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FEA Approach for Wear and Damage Prediction of Tools for the Progressive Die Stamping of Steel Washers

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Abstract. In progressive die stamping processes, maintenance activities caused by tool damage, and wear represent economic losses for companies. An effective predictive maintenance strategy can only be implemented if maintenance data coming from the operations are correlated to specific process-related information. As a part of a more general data-based predictive maintenance strategy, the main causes of tool damage and wear in a progressive die stamping factory that produces automotive metal washers have been identified by means of FEA simulations. In this study, the progressive die stamping of a dented conical washer is simulated with Transvalor FORGE FEA software by implementing the process parameters used in a real case. In this study, two indicators called FEA_{wear} and FEA_{damage} are proposed for prediction of die wear and damage for tools with high risk of failure. For validating the accuracy of the FEA simulations, dimension and geometry comparisons are performed between FEA and real washer, and then real and FEA maximum press force comparison is performed. In the end, FEA simulations demonstrated their accuracy in predicting the stamping force of the press and the final part quality, and proposed FEA damage and wear indicators accurately predicted the most critical tools and stations, as confirmed by the real maintenance data. Finally, the simulations also correctly detected potential damage zones of the tools.

1. Introduction

Progressive die stamping is a manufacturing solution highly employed by many industries for its high dimensional accuracy of final parts, high productivity, and reduced maintenance costs. In progressive die stamping processes, maintenance activities caused by tool damage, and wear represent strong economic losses for companies, because tens or hundreds of tools operate simultaneously, and the stroke rate can be very high (up to hundreds or even thousands of strokes per minutes [1]).

While planned maintenance on tools (by replacement or sharpening) has limited effects on the productivity, unplanned maintenance due to an unpredicted tool failure has severe consequences on both quality and production costs. In fact, a progressive die stamping process is characterized by a series of stations; each station typically performs a specific mechanical operation on the sheet metal.

An effective predictive maintenance strategy can only be implemented if maintenance data coming from the operations are correlated to specific process-related information. As a part of a more general data-based predictive maintenance strategy, the most relevant and frequent causes of tool damage and wear in a progressive die stamping factory must be first identified. Wear, and damage are complex phenomena that are related to many parameters such as tribology, material mechanical properties, geometry. However, for an efficient implementation, few and simple indicators of failure must be determined, and this can be done only if the study is restricted to a very specific geometry and material type.

The present study is restricted to the production of automotive carbon steel washers. The purpose of the present study is to identify simple, compact but reliable indicators for the FEA prediction of both progressive wear and failure by damage accumulation, aimed at highlighting the high-risk tools, i.e., the tools with a high risk of sudden/unpredicted failure. The FEA-based indicators can be used to select the most appropriate typology and location of tooling sensors to be used in a data-based predictive maintenance approach.

Hoffman et al. simulated wear behavior both qualitatively and quantitively for deep drawing, using REDSY simulation tool and compared the results with experiments, discovering that they were in good agreement. [2] Another study also showed the accuracy of FE-model for predicting wear phenomenon in the open shear-cutting process by considering the different wear coefficients, supporting simulations results with experiments [3]. Hatanka et al. studied sheet blanking process using self-developed rigid-plastic FEM code that follows the node separation method for crack initiation and propagation simulation. The study also conducts experiments to support the validity of FE simulation, focusing mainly on the edge areas where crack propagation could be properly observed. The results of experiments agreed with the simulations [4]. Abdulla Mohammad Gous Shaikh Rao used the software LS-DYNA to study the design of forming tools for girder forming with a goal of avoiding cracks and severe wrinkling and they achieved a stable, damage-free forming process without cracks or severe wrinkling using the software. LS-DYNA allowed them to predict and solve failures and weak-points during design or manufacturing phases [5]. The ductile tearing behavior of a 0.8 mm thick ultra-thin martensitic stainless steel was probed in a blanking process by Wang et al. As a result of experiments and simulations, the authors concluded that micro-voids did not develop sufficiently before fracture, signifying that growth and evolution micro-voids were not the primary cause for fracture. The shear damage was found to be the main factor for material the failure and it was discovered that fracture first appeared at punch edge on the symmetrical surface. Crack propagation occurred after this towards free surface along the largest damage path [6]. Subramonian et al. presented a methodology to obtain high strain and strain rate based on the material flow stress data by using experiments and FE modelling. FE study showed that, at high strains, to model high speed blanking, temperature and strain rate dependent material model was needed. FE also showed that blanking alone was capable testing material flow stress data generation at high strains and strain rates [7]. As it can be seen in the literature, FEA can be a great asset for analysis, prediction, optimization and modelling of manufacturing processes, especially when supported by data.

2. Case Study

In this study, a dented conical washer made of C60 steel (Fig.1) is produced from a 1.8 mm thickness blank with a mechanical press running at 500 rpm.

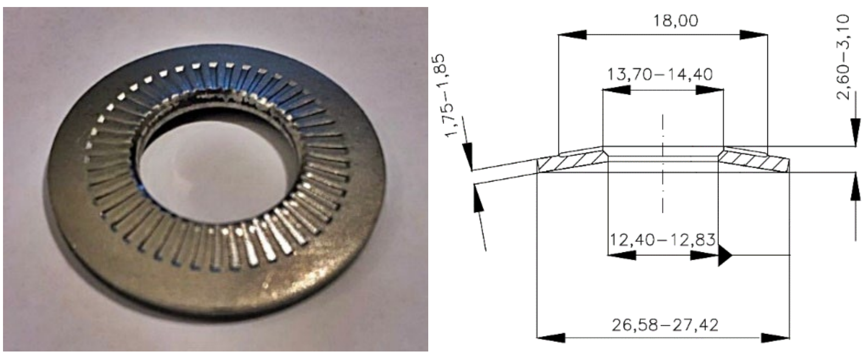

Figure 1: Conical dented washer geometry and dimensions

The whole progressive die stamping process of punching, chamfering, coining, and blanking (Fig.2) is simulated using Transvalor FORGE, a non-linear solver with implicit time integration scheme. Then, FEA simulation accuracy is validated by comparison of washer geometry, and dimensions.

The simulations have been conducted twice, both considering the elastic deformation of the tools and considering the tools fully rigid. Only half of the stations are simulated by considering a symmetry plane to reduce simulation time without a loss of result accuracy. The tool materials and properties are given in Table 1.

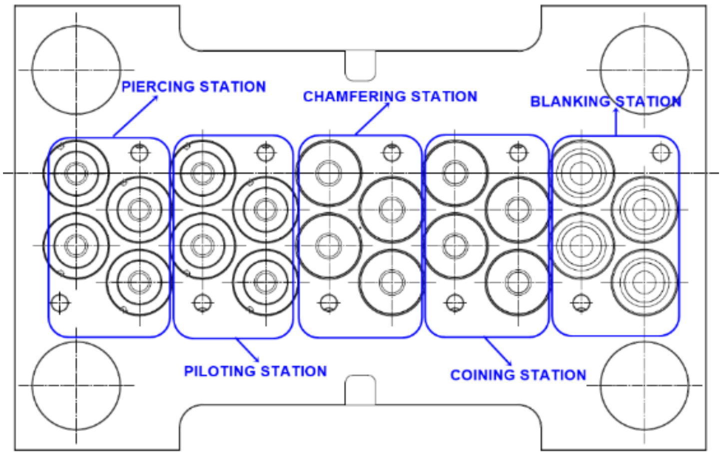

Figure 2: Layout of the punches in the upper die holder plate

Table 1: Die material properties

	Tool material			Coating	
	Material	Young's modulus [MPa]	Yield Stress [MPa]	HV hardness	Residual Stress [MPa]
Punching Punch	G4	520000	2545	3200	3000
Punching Die	G4	520000	2545	3200	3000
Chamfering Punch	1.3343	226500	2185	3000	3000
Chamfering Die	G4	520000	2545	3200	3000
Coining Punch	1.3343	226500	2185	3000	3000
Coining Die	1.3343	226500	2185	3000	3000
Blanking Punch	G4	520000	2545	3200	3000
Blanking Die	G4	520000	2545	3200	3000

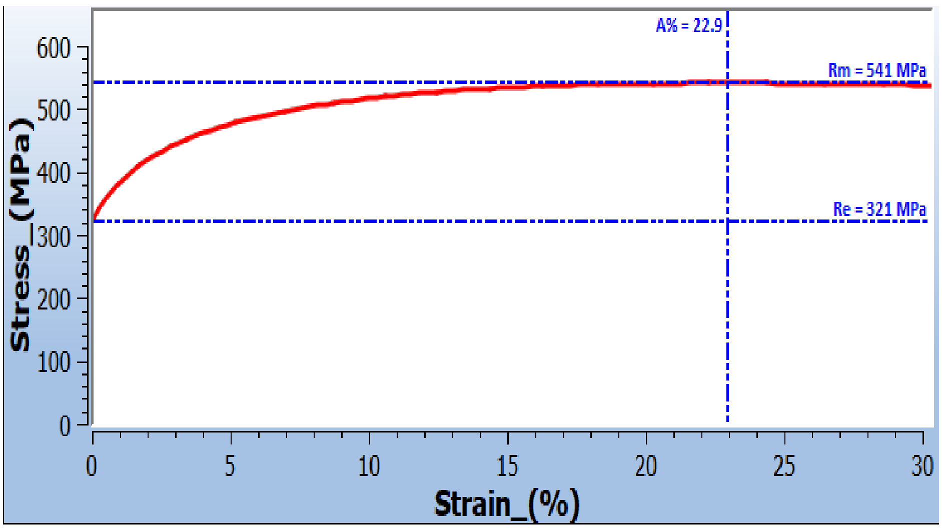

Figure 3: Stress-strain curve of C60 sheet material

Sheet metal material is isotropic C60 steel, with the hardening curve shown in Fig. 3 modeled with the Hansel-Spittel equation with no strain rate or temperature effects. The C60 properties have been assessed by tensile tests. The blank (sheet) is given a self-contact option to prevent it passing through itself in case of folds. The friction between sheet and tools is oil lubrication, modeled through a Tresca-limited Coulomb friction, with Coulomb coefficient μ assumed at 0.1 (which is a typical value) and Tresca friction factor $\overline{m}$ assumed at 0.2. The heat exchange between the tools and sheet is assumed at 2000 W/m^{2}K (as suggested by the software default value for weak exchange). All tools and sheet are at room temperature (20 °C).

Meshing is performed with automatic remeshing for sheet and tools. In the deformation or shearing zones a fine tetrahedron mesh of 0.24 mm is used by creating meshing boxes. Remeshing on deformation was activated with a trigger size value of 0.4 mm. A sample mesh can be seen in Figure 4.

For punching, and blanking stations, Latham & Cockcroft Normalized (LCn) damage model was activated to view shearing via element deletion method with threshold value of LCn 0.4 with high smoothing option active for achieving the most accurate smooth cut surface. LCn method was also active for plastic deformation operations of other stations, and this parameter was used to support the proposed damage indicator, FEA_{damage}, and to support prediction of risky damage zones by FEA.

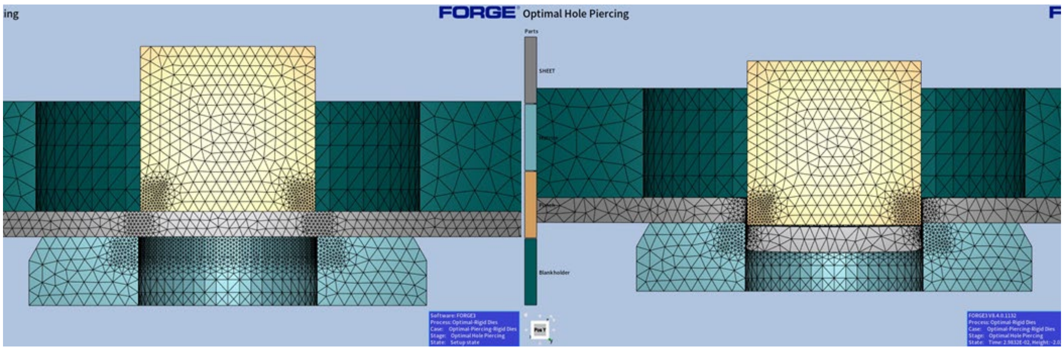

Figure 4: Fine meshing zones, and coarse meshing in punching station

3. Definition of FEA Damage and Wear Indicators

In this section we proposed two new risk indicators for progressive wear, and failure by fracture.

In the literature, it is possible to find different abrasion wear models. Archard's model is a common and simple wear model that is both used for two-body abrasion wear, three-body abrasion wear and sliding wear [2]. In this model, the wear volume W [mm^3] is described as dependent on a wear coefficient K, normal force, tool hardness and sliding distance. Determination of K requires experimentation with specified conditions. When the experimentation is not feasible or available, the assumption of wear coefficient K for wear calculation by using Archard model or any of its modifications might cause inaccuracies due to its unpredictable nature and dependence on many parameters such as material combination, relative humidity, load, speed, location, temperature, geometry, lubrication. [8]. For this reason, in this study a FEA parameter, FEA_{wear}, is proposed to predict wear risk (see equation 1).

$$FEA_{wear} = \frac{\tau_{max}}{HV_{coating}} \qquad (1)$$

where τ_{max} [MPa] is the highest shear stress acting on the tool surface during stamping process, and $HV_{coating}$ [MPa] is the Vickers hardness value of the die coating (Table 1). When two surfaces slide across each other, shear stress is exerted on their surface, and shear stress also considers the friction and contact pressure. For these reasons, and after trials with other result parameters as well, division of maximum shear stress value with the Vickers hardness value of the dies gave accurate results, based on the corrective maintenance data of wear in the real case.

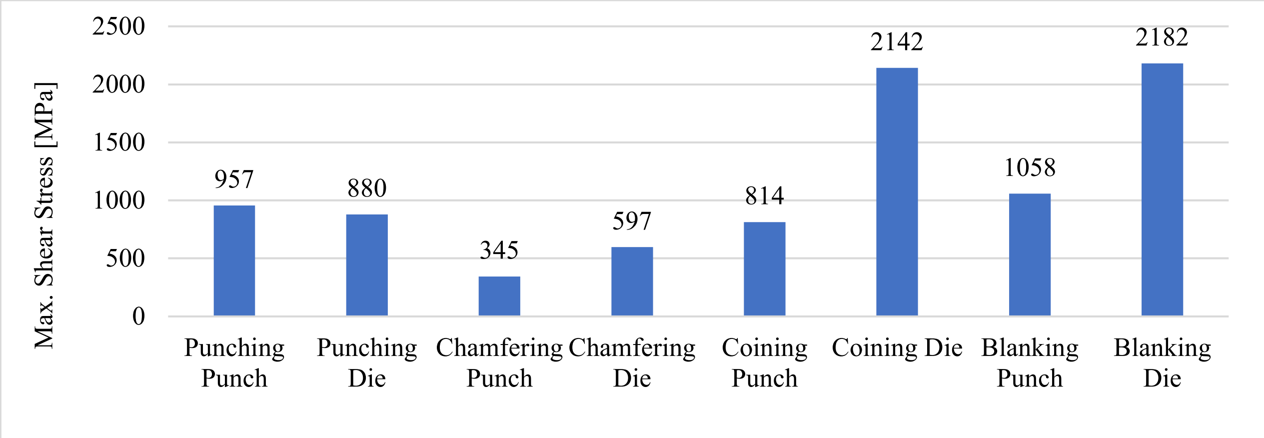

Figure 5: Maximum shear stress values on the tools for each station

Based on Table 1 and Figure 5, FEA_{wear} values are as follows.

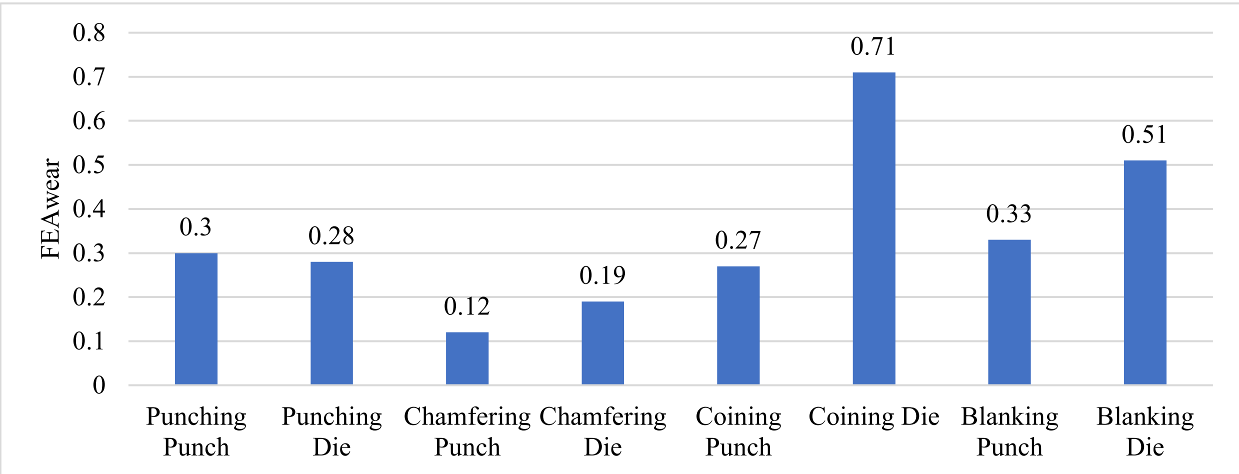

Figure 6: FEA_{wear} values per station

A common method used to study damage in FEA is the Latham & Cockcroft Normalized (L&C) indicator (see equation 2). L&C normalized parameter was also implemented in FORGE and, as the present study confirms, works very well in predicting the risk of tool failure. This indicator considers first principal stress (σ_1), Von Mises stress (σ_{VM}), and strain rate $\bar{\varepsilon}$.

$$Normalized\ L\&C\ Damage = \int \frac{\sigma_1}{\sigma_{VM}} d\bar{\varepsilon} \qquad (2)$$

In this study, the use of L&C normalized is complemented by a newly developed indicator, FEA_{damage}, which helps highlighting the tools with the highest risk. The proposed FEA_{danage} indicator for predicting risky tools considers maximum Von Mises stress detected on the tools ($\sigma_{VM,max}$), coating residual stress ($\sigma_{res,coating}$), and the yield stress of the die ($\sigma_{o,die}$). For this indicator, $\sigma_{VM,max}$ is an FEA parameter. $\sigma_{res,coating}$ is a real case value and it is calculated by converting compressive residual stress (σ_{III} = -3 GPa) introduced by the coating to a scalar value by using Von Mises stress equation where σ_I and σ_{II} were assumed to be zero. Yield stresses and residual coating stress values of the tools can be viewed in Table 1. $\sigma_{VM,max}$ considers all principal stresses. If the σ_{VM} value of a point exceeds $\sigma_{o,die}$, it is in the plastic region and repeated loading would eventually lead to a crack initiation. However, coating induced compressive residual stress also plays a role for resistance against damage. Therefore, a method for calculation of damage indicator is proposed. According to FEA_{damage}, if σ_{VM} value on a die exceeds $\sigma_{res,coating}$, that would mean there is a risk of undergoing failure, otherwise there is no risk. In case of existence of failure risk, its likelihood is expressed by considering also the die yield stress, by dividing ($\sigma_{VM,max}$- $\sigma_{res,coating}$) by $\sigma_{o,die}$. This is expressed in equation (3).

$$FEA_{damage} = \frac{\sigma_{VM,max}-\sigma_{res,coating}}{\sigma_{0,die}} \qquad \text{if } \sigma_{VM,max} \geq \sigma_{res.coating} \qquad (3)$$

$$FEA_{damage} = 0 \qquad \text{if } \sigma_{VM,max} < \sigma_{res.coating}$$

Table 2: $\sigma_{VM,max}$ values of tools

	Punching Punch	Punching Die	Chamfering Punch	Chamfering Die	Coining Punch	Coining Die	Blanking Punch	Blanking Die
Max. Von Mises Value [MPa]	1772	1591	598	1243	1457	3912	2017	3381

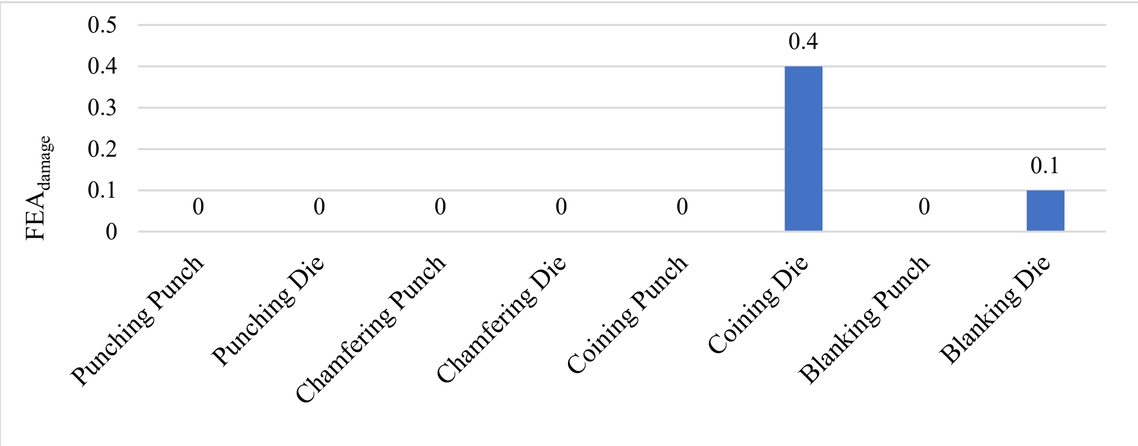

Figure 7: FEA_{damage} indicator of tools

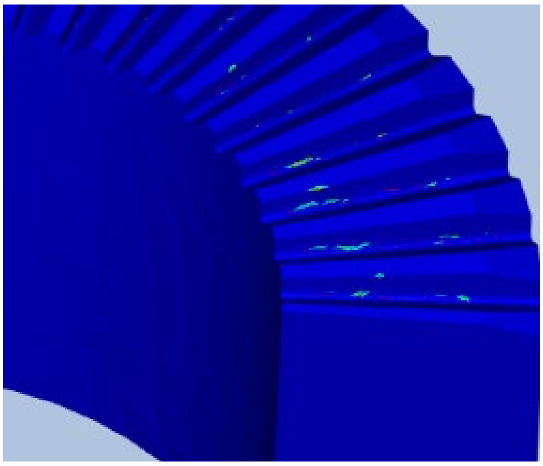

Figure 8: FEA high Von Mises stress areas on coining die

4. Results and Comparisons

The accuracy of the FEA simulations is supported by comparisons between real washer and FEA washer based on geometry, dimensions, and total press force. The comparisons below show that simulations were indeed successful in producing an accurate part, with press force in range between real maximum and average value.

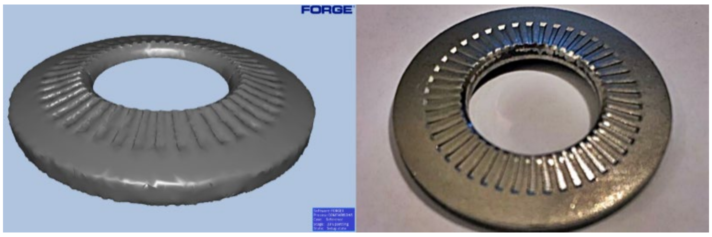

Figure 9: Geometry comparison between FEA washer and real washer

Table 3: Dimension comparison between FEA washer and real washer

	External Diameter(mm)	Internal Diameter(mm)	Thickness(mm)	Height(mm)
Real Washer Max	27.4	12.8	1.85	3.1
Real Washer Min	26.6	12.4	1.75	2.6
FEA Washer	26.6	12.5	1.8	3.0

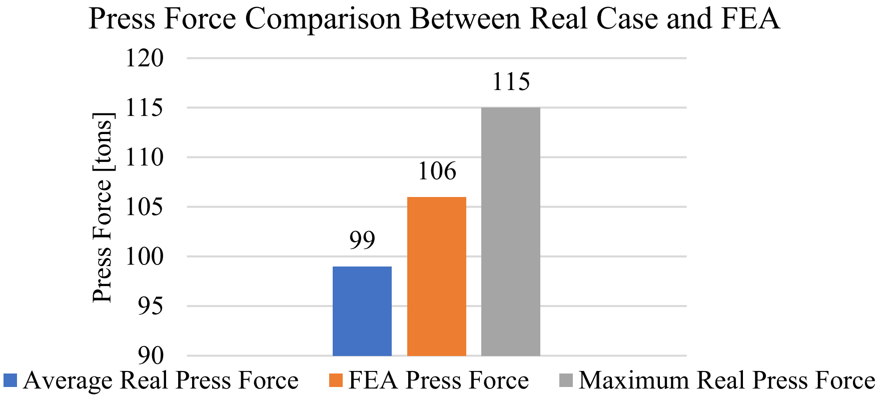

Figure 10: Press force comparison between real case and FEA

Maintenance data from a real industrial press in operation were collected during a period of 4 years (2016-2020) and 50 maintenance reports, corresponding to the production of 88513000 washers. Comparisons between FEA_{wear} and the maintenance data due to wear (Figure 11) showed that, proposed FEA wear indicator successfully predicted the most critical die (that is more likely to be worn) as the coining die. The maintenance data shows only corrective maintenance, we were informed that out-of-production hours preventive maintenance for the other stations such as tool sharpening was also performed, which explained why there were not many maintenance interventions for the other stations during production hours. Preventive maintenance was not possible for coining die since it has a complex shape and teeth height is small, around 0.12 mm, therefore they cannot be sharpened. As it was mentioned before, Archard wear model is commonly used for wear studies, and this parameter was also implemented in FORGE. However, this parameter is not used in this study due to lack of information about K coefficient, and because it was only possible to enter one hardness value for all tools and sheet whereas this is not the real case.

FEA_{damage} indicator successfully predicted the tool at highest risk of damage as "coining die" as was the case in the maintenance data (Figure 12). L&C normalized values of the tools (Figure 12) also indicated the coining die as the tool with the highest risk of fracture. A combination of both parameters can well predict the real industrial maintenance requirement. In fact, while the L&C indicator is well correlated with the maintenance requirements of the coining and blanking dies, it overestimates the requirements on the punching and chamfering tools. Although, it must be stated again that punching, chamfering, and blanking tools are subjected to preventive maintenance regularly and data corresponds only to corrective maintenance.

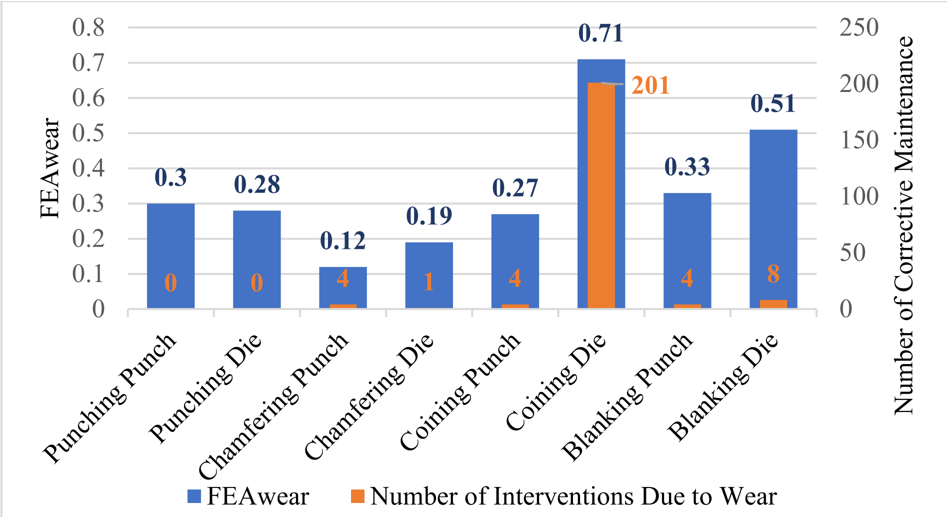

Figure 11: FEA_{wear} values per station, and comparison between FEA_{wear} indicators and corrective maintenance data

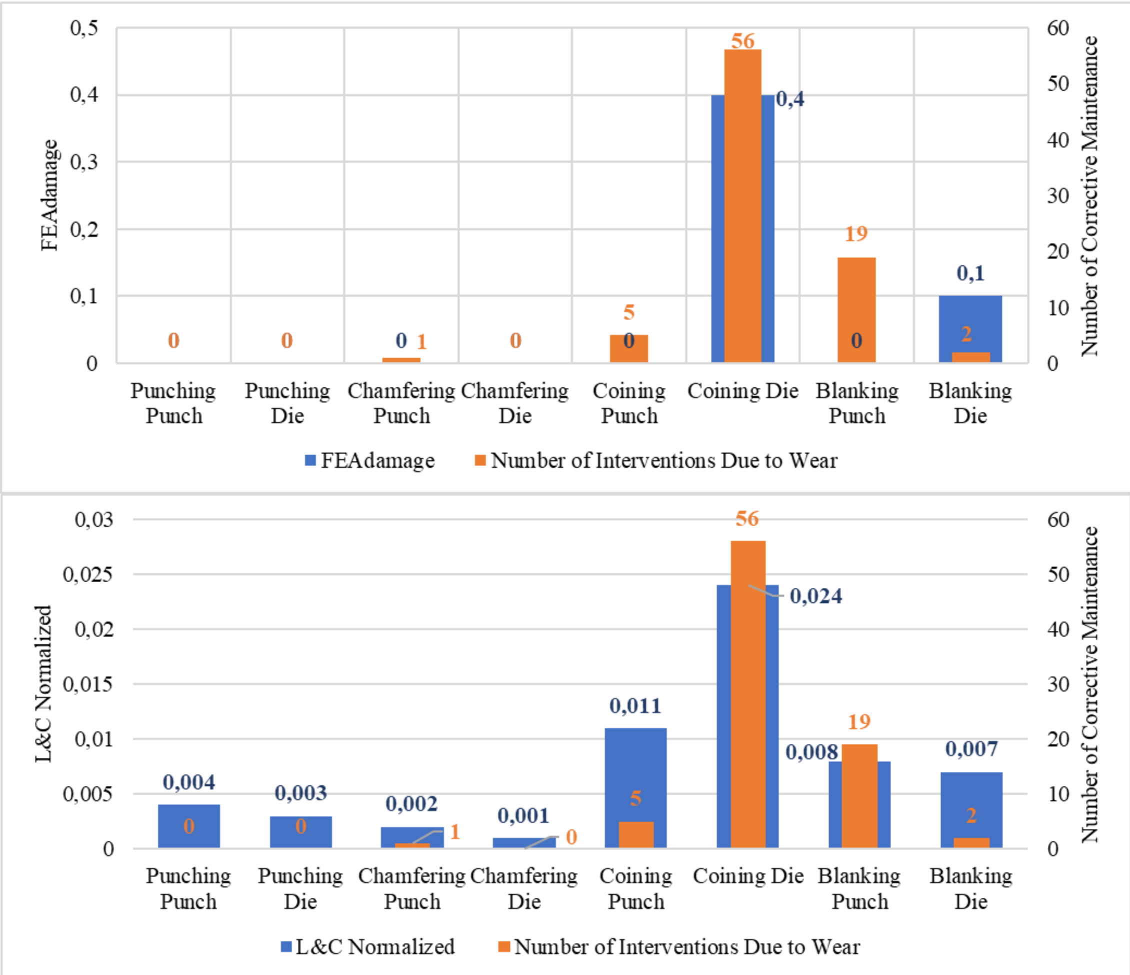

Figure 12: Comparison between FEA_{damage}, L&C Normalized, and corrective maintenance data for damage

On the contrary, the FEA_{damage} indicator correctly estimates the negligible maintenance efforts required by the punching and chamfering tools, correctly estimates the requirements of the coining die, but it underestimates the requirements of the blanking tools. A possible reason for this is that in the real process horizontal misalignment of the sheet (swording) caused blanking pilot to contact the blank, thus making it worn or damaged in time whereas in simulations the tools and the blank were perfectly aligned, and pilot does not contact the sheet. A sensitivity analysis conducted with FORGE by misaligning tools and sheet, supported this reasoning as can be seen in Figure 13.

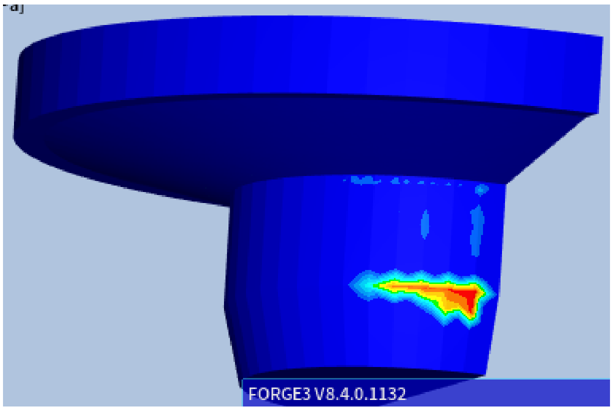

Figure 13: Misalignment (swording) effect on the blanking pilot

Similar analyses, here not reported in the paper for brevity, have been conducted with two more case studies, i.e., two more steel washers (pictures given in Fig. 14). Both of them are similar, i.e., they are washers. The proposed wear and damage indicators were well correlated to the real maintenance data of these two components as well.

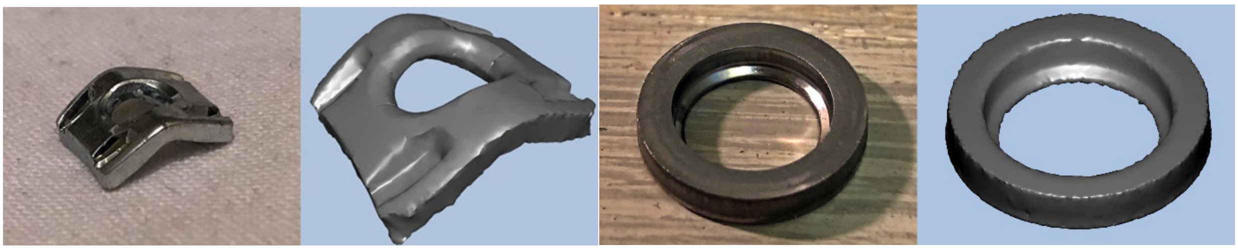

Figure 14: Additional case studies

5. Conclusions

In cases where experiments would prove too costly and long, and when real-case data is available such as maintenance data, FEA simulations can be a good alternative solution as long as simulation parameters are inserted accurately. This study showed that:

- FEA simulations conducted by Transvalor FORGE based on process parameters of the real progressive die stamping, successfully produced conical dented washer as validated by geometry, dimension, and press force comparisons.
- Proposed FEA_{wear} indicator predicted the riskiest tool for wear as "coining die" which was confirmed by corrective maintenance data. Therefore, FEA_{wear} indicator was accurate for prediction of dies with high wear risk provided that maximum shear stress on the tools, and Vickers hardness values are known.
- Proposed FEA_{damage} indicator predicted the riskiest tool for damage as "coining die" which was confirmed by maintenance data and L&C normalized values of tools. Therefore, FEA_{damage} indicator was accurate at predicting riskiest dies in terms of damage. Moreover, it was shown that combination of FEA_{damage} and L&C normalized indicators can help prediction of risky tools to help planning maintenance priorities.
- FEA simulations showed high Von Mises stress concentrations on teeth base in "coining die", and that is where "tooth breakage" occurred in the real case during production. Therefore, FEA is also a useful tool to have an opinion about risky damage zones.

The proposed indicators are simple but can be effectively used for the specific production of the presented case study. They represent a little step of a broader and more ambitious framework which aims at implementing an "Industry 4.0" monitoring and predictive maintenance strategy, which will combine: force and pressure and other sensors signals coming from the presses, maintenance data coming from the "tooling" department, statistical process control (SPC) data coming from the "quality" department.

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