Pre-publication draft of paper accepted for publication in the Proceedings of the IASTED International Conference on Artificial Intelligence and Applications (AIA 2002), pages 155-159.
Publisher: ACTA Press

Fault detection in a cold forging process through feature extraction with a neural network

B. F. Rolfe[1], Y. Frayman[1], P. D. Hodgson[2], G. I. Webb[1], G. L. Kelly[2]
[1]School of Computing and Mathematics
Deakin University
Geelong, Vic. 3217, Australia
[2]School of Engineering and Technology
Deakin University
Geelong, Vic. 3217, Australia
email: {brolfe,yfraym,phodgson,webb,glkelly}@deakin.edu.au

Abstract

This paper investigates the application of neural networks to the recognition of lubrication defects typical to an industrial cold forging process employed by fastener manufacturers. The accurate recognition of lubrication errors, such as coating not being applied properly or damaged during material handling, is very important to the quality of the final product in fastener manufacture. Lubrication errors lead to increased forging loads and premature tool failure, as well as to increased defect sorting and the re–processing of the coated rod. The lubrication coating provides a barrier between the work material and the die during the drawing operation, moreover it needs be sufficiently robust to remain on the wire during the transfer to the cold forging operation. In the cold forging operation the wire undergoes multi–stage deformation without the application of any additional lubrication. Four types of lubrication errors, typical to production of fasteners, were introduced to a set of sample rods, which were subsequently drawn under laboratory conditions. The drawing force was measured, from which a limited set of features was extracted. The neural network based model learned from these features is able to recognize all types of lubrication errors to a high accuracy. The overall accuracy of the neural network model is around 98% with almost uniform distribution of errors between all four errors and the normal condition.

Keywords: *Lubrication defects, fasteners manufacturing, cold forging, neural networks, feature extraction*

1 Introduction

Cold forging includes many processes such as bending, cold drawing, cold heading, coining, extrusion, punching, and thread rolling to produce a diverse range of part shapes. These include various shaft-like components, cup-shaped geometry parts, hollow parts with stems and shafts, all kinds of upset (headed) and bent configurations, as well as combinations of these geometries. The temperature of metals being cold forged may range from room temperature to several hundred degrees.

Often chosen for integral design features, such as built-in flanges and bosses, cold forging is frequently used in automotive steering and suspension parts, antilock-braking systems, hardware, defense components, and other applications where high strength, close tolerances and volume production makes it an economical choice.

In the cold forging process, a chemically lubricated slug is forced into a closed die under extreme pressure. The unheated metal thus flows into the desired shape.

Upsetting, or heading, a common technique for making fasteners, gathers steel in the head and other sections along the length of the part. In upsetting, the metal flows at right angles to the ram force, increasing the diameter and reducing the length.

A typical fastener manufacturing process uses batch production material transfer. The plant is divided into three main areas:

- Pre–processing that involves descaling and application of lubrication consisting of the zinc phosphate carrier and a soap stearate lubricant coating;
- Primary processing that involves wire drawing and extrusion;
- Post–processing that involves cleaning, heat treatment and the application of a protective coating.

This paper investigates the application of neural networks to the recognition of lubrication defects typical to an industrial cold forging process employed by fastener manufacturers. The accurate recognition of lubrication errors, such as coating not being applied properly or damaged during material handling, is very important to the quality of the final product in fastener manufacture.

The lubrication used during pre–processing has a major impact on the productivity of the primary processing area. For example, if pre–processing fails to produce high quality coated rod or the coating is damaged during the material handling then the output efficiency of the primary processing is decreased. This is a result of increased forging loads and premature tool failure, as well as increased defect sorting and the re–processing of the coated rod. The lubrication coating must provide a barrier between the work material and die during the drawing operation, while still be sufficiently robust to remain on the wire during the transfer to the extrusion operation, where the wire undergoes multi-stage deformation without the application of additional lubrication.

Four types of lubrication defects, typical to production of fasteners, were introduced to a set of sample rods, which were subsequently drawn under laboratory conditions. The drawing force was measured, from which a limited set of features was extracted. The neural network based model was learned from these features to be able to distinguish all types of lubrication errors from the normal condition.

2 Test Rig

The main measures to evaluate lubrication coating performance are tooling change–over rates and the detection of score marks appearing on drawn and forged surfaces.

The evaluation of the coating performance is done usually through production based methods. These production evaluation techniques, while being a valuable long term indicator of coating performance, are reactive methods and are unable to assess the coating condition before it enters the primary processing area. This leads to tooling and product damage.

The evaluation technique developed at the School of Engineering and Technology, Deakin University [2] (Fig. 1) uses a process simulation test rig and a selection of analysis tools to evaluate the coating performance. This technique allows lubrication evaluation to be performed in isolation to production, enabling analysis to be done without interfering with day–to–day running of the production line.

The main performance requirements for the lubrication coating are from the pre–forge wire drawing operation and the extrusion stages in the cold forging process. In the current approach, these stages in the fastener manufacturing process are simulated by multi–reduction drawing. The first reduction simulates the pre–drawing process while a second reduction simulates the extrusion stage of the cold forging process [2]. The test rig was constructed from a variable speed, continuous drawing machine where quick–change multi–reduction die hostings, quick–change rod clamping mechanism and constrained flat bed were designed and installed. Strain gauges were mounted at the rod clamping mechanism to detect drawing force at both the first and second reductions. Force signals are collected and conditioned by National Instruments hardware and Labview software. In this paper we deal with pre–forge wire drawing operation only.

Figure 1. The multi–draw test rig

3 Experimental Set–Up

A two layer solid lubricant system was used on the rods. This was applied in a plant environment with conditions kept as close as possible to those used for standard production. The experimental test rig was used to produce the rod samples drawn with a 0.35mm reduction from the a starting diameter of 5 mm.

50 samples were produced with 2 layer coating applied: zinc phosphate carrier and calcium stearate lubricant coating. Another 20 samples were produced as before but with an additional coating of soap lubricant. This final coat of powdered lubricant was added to minimize the damage of the sensor's drawing die on the production wire the same way as it is done in plant.

Four different kinds of defects common in production of fasteners, were introduced into the coatings (Fig. 2):

1. No coating, where heat shrink wrap was applied to rods prior to all steps in the coating process. This corresponds to missing coatings from a pre–processing stage;

2. Zinc phosphate only, where heat shrink wrap was applied after the zinc phosphate application. This corresponds to the missing calcium stearate layer coating from a pre–processing stage;

3. Hammer peening of the surface of the bar. This type of error simulates defect introduced during material handling from pre–processing area to the primary processing;

4. Scratching of the coating by its removal parallel to the bar, which was introduced by filing the coating off. This type of error simulate coils being dragged across the shop–floor during transfer from pre–processing area to the primary processing.

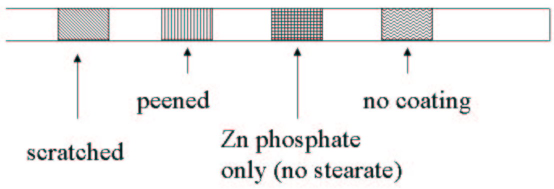

Figure 2. Sample rod

All defects were approximately 50mm in length and applied to the circumference of the rod with defects being separated by fully coated lengths of rod.

The samples were drawn with an area reduction of approximately 7% and the loads on the drawing die were monitored by strain gauges on the rod clamping mechanism. All defects resulted in increased drawing loads. In the case of the hammer peening, this is likely to be due to the resulting irregularity of the rod diameter. In the other three cases, reduced efficiency of the coatings is due to missing lubrication components. The defect with only zinc phosphate layer resulted in the highest friction. The zinc phosphate is a soft coating and thus is likely to produce a galling or sticking effect as the rod passed through the die.

The typical force signatures for the rods with two–layers of lubricants (labeled as non–lubricated samples) and for the rods with an extra layer of lubricant applied (labeled as the lubricated samples) are shown in Figs. 3 and 4.

As can be seen, the error 4 (scratching of the coating) is visually indistinguishable from the normal condition (the one without any errors) on non-lubricated data, and only the error 3 (peening of the surface of the bar) is readily distinguished from the normal condition on the lubricated data.

The force signatures were collated to create two time series, one for non–lubricated samples, and another for lubricated samples with all five possible lubricant conditions (normal condition and the four defects) appropriately pre–labeled with a corresponding condition label being manually applied to each time step of the drawing force signal.

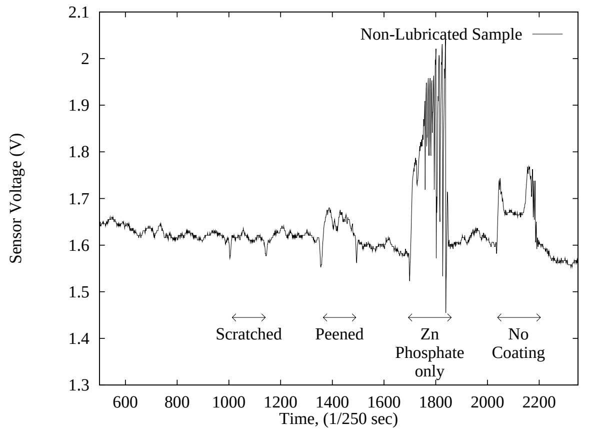

Figure 3. Typical non–lubricated rod sample

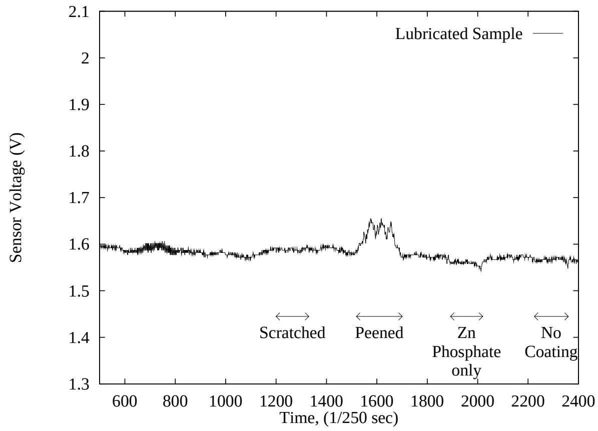

Figure 4. Typical lubricated rod sample

4 Experimental Results

The main aim of this paper is to develop an inductive model to identify accurately the lubrication errors in the cold forging by analyzing a force signature. That is, force variations from the nominal values are to be linked to various lubrication defects.

There are several possible approaches to the development of such a model. The most common approach is to formulate the problem as a classification (pattern recognition) problem [1].

We are interested in separating accurately the normal condition from all four types of lubrication defects. However, a single drawing force value reveals very little information about what sort of condition the process is in. This limitation can be alleviated by extracting some useful features from a set of contiguous force values

$$f_i = P_j(\{x_i, ..., x_{i+n}\}) \ ,$$

where f_i is the feature, P_j is the jth feature extractor function, x_i is the first force value of the set, x_{i+n} is the last force value of the set and n is the size of the set.

The set of force values is defined as a sliding window. Associated with each sliding window is the lubrication condition or the output class:

$$h(\{f_1, ..., f_m\}) \in \{\text{normal condition}, \text{error1}, ..., \text{error4}\} \ ,$$

where $h(.)$ is the lubrication condition, and $f_1, ..., f_m$ are the extracted features of the window.

Therefore, we can associate each sliding window and its features with a corresponding lubrication condition. The true lubrication condition was chosen to be the output class associated with each sample point, x_{i+n} of the sliding window. In this case, the sliding window always extracts features from the past drawing force data. The size of a sliding window was 300 time steps and selected based on the minimal root–mean–square error between the predicted condition by the model and the actual condition of the lubricant.

The usefulness of the features extracted from the drawing force signal was analyzed by sensitivity analysis to evaluate their impact on the recognition rate for each condition and only the most important ones were retained.

The following features were selected:

- Maximum force value within a sliding window;
- Minimum force value within a sliding window;
- Arithmetic mean (average) force value within a sliding window;
- Geometrical mean (median) force value within a sliding window;
- Standard deviation of the force values within a sliding window. This is a measure of how widely force values are dispersed from the average force value (the mean);
- Average deviation of the force values within a sliding window. This is a measure of the variability in a data set. It is the average of the absolute deviations of force data points from their mean;
- Skewness of the force values within a sliding window. This characterizes the degree of asymmetry of a force data distribution around its mean;
- Kurtosis of the force values within a sliding window. This characterizes the relative peakedness or flatness of a force data distribution compared with the normal distribution;
- Correlation between the force values within the current and the previous sliding windows;
- Covariance between the force values within the current and the previous sliding windows. This is the average of the products of deviations for each force data point pair.

In addition to extracted features we also used the current force signal and the past force signals with different time delays ranging from 25 time steps to 400 time steps also selected based on the minimal root–mean–square error between the predicted condition by the model and the actual condition of the lubricant.

The output sensitivity values for each of the model inputs are in Table 1.

As an inductive model within a patter recognition framework we used a feedforward multilayer perceptron (MLP) with backpropagation learning algorithm with a momentum term.

An attractive feature of MLP network is that, given the appropriate network topology and the rigorous training procedures, they are capable of reliably characterizing nonlinear functional relationship [4]. As the activation function of the MLP model we used a hyperbolic tangent. A pattern (on–line) learning and early stopping was employed. All input variables were normalized with zero mean unit average normalization.

The optimal parameters of the MLP were selected based on preliminary experiments. The parameters which resulted in smallest root–mean–squared–error between the predicted lubrication conditions and the actual lubrication conditions, were used. The selected MLP model consisted of 20 inputs and 5 outputs with two hidden layers, the first hidden layer has 50 nodes, and the second hidden layer has 45 nodes. The learning rate selected was 0.05, the momentum term was 0.99.

An oversampling of the lubrication defect data points was utilized to create an equal distribution of data tuples for each lubrication condition to avoid the problem of small disjunct [3, 5] as the data for the normal condition of lubrication (the one without any defects) dominates the available data tuples (being around 75% of all available data tuples). The data tuples were selected randomly, with 70% used for training and the remaining 30% to test the model generalization ability.

The overall prediction results of the MLP model and the corresponding confusion matrices are in Table 2.

From the Table 2 it is clear that the performance of the MLP model is extremely accurate. The MLP model is able to distinguish perfectly, apart from a single exception, the boundaries between all the errors and only has some difficulty with recognition of the boundaries between the normal conditions and the errors. Even these boundaries are recognized with a very high accuracy being between 97% and 99%. Most importantly, while the extra layer of calcium stearate

Table 1. Output sensitivities for each of the model input variables. Here the sens1 represents the sensitivity for the normal condition, while the sens2 to sens5 represents the sensitivities for errors 1 to 4

	Non–lubricated samples					Lubricated samples				
input	sens1	sens2	sens3	sens4	sens5	sens1	sens2	sens3	sens4	sens5
Force	0.0701	0.0632	0.0552	0.0585	0.0609	0.0422	0.0503	0.0338	0.0661	0.0535
Force (delay 25)	0.0473	0.0539	0.0511	0.0418	0.0440	0.0454	0.0362	0.0559	0.0506	0.0369
Force (delay 50)	0.0376	0.0334	0.0335	0.0259	0.0434	0.0403	0.0371	0.0398	0.0442	0.0360
Force (delay 100)	0.0355	0.0404	0.0245	0.0270	0.0308	0.0213	0.0212	0.0225	0.0226	0.0283
Force (delay 150)	0.0328	0.0374	0.0449	0.0326	0.0316	0.0425	0.0328	0.0409	0.0546	0.0274
Force (delay 200)	0.0410	0.0405	0.0621	0.0416	0.0456	0.0332	0.0275	0.0378	0.0354	0.0272
Force (delay 250)	0.0584	0.0419	0.0504	0.0430	0.0507	0.0386	0.0399	0.0355	0.0496	0.0386
Force (delay 300)	0.0612	0.0633	0.0655	0.0513	0.0614	0.0423	0.0358	0.0324	0.0510	0.0368
Force (delay 350)	0.0596	0.0635	0.0674	0.0838	0.0389	0.0676	0.0712	0.1073	0.0695	0.0665
Force (delay 400)	0.0404	0.0397	0.0451	0.0421	0.0501	0.0817	0.0768	0.0859	0.0701	0.0914
Max	0.0696	0.0473	0.0612	0.0867	0.0865	0.0806	0.0953	0.0758	0.0697	0.0800
Min	0.1026	0.0769	0.0842	0.1068	0.1111	0.1481	0.1303	0.1326	0.1248	0.1637
Average	0.0312	0.0465	0.0315	0.0412	0.0314	0.0355	0.0362	0.0396	0.0301	0.0399
Median	0.0415	0.0546	0.0387	0.0481	0.0468	0.0225	0.0284	0.0246	0.0214	0.0234
Stdev	0.0459	0.0376	0.0364	0.0411	0.0585	0.0572	0.0701	0.0468	0.0481	0.0502
Avedev	0.0275	0.0313	0.0365	0.0229	0.0292	0.0561	0.0695	0.0477	0.0488	0.0505
Skew	0.0538	0.0574	0.0612	0.0526	0.0507	0.0389	0.0396	0.0371	0.0394	0.0393
Kurt	0.0640	0.0692	0.0631	0.0619	0.0580	0.0632	0.0650	0.0609	0.0601	0.0654
Correl	0.0295	0.0433	0.0317	0.0310	0.0259	0.0241	0.0195	0.0218	0.0256	0.0262
Covar	0.0506	0.0585	0.0560	0.0601	0.0444	0.0187	0.0173	0.0211	0.0182	0.0185

Table 2. Model prediction results for each of the process conditions. Here Normal represents the normal condition, Error 1 represents no coating, Error 2 represents the zinc phosphate layer only, Error 3 represents peening and Error 4 represents scratching

	Non–lubricated samples					Lubricated samples				
Lub condition	Normal	Error 1	Error 2	Error 3	Error 4	Normal	Error 1	Error 2	Error 3	Error 4
Recognition rate	97.2%	99.4%	98.6%	99.2%	99.4%	97.5%	98.6%	98.7%	98.7%	98.1%
Confusion matrices	13854	9	19	9	6	11380	12	12	13	15
	95	1511	0	0	0	60	876	0	0	1
	68	0	1381	0	0	67	0	888	0	0
	87	0	0	1059	0	73	0	0	1018	0
	152	0	0	0	1028	97	0	0	0	830

coating applied to lubricated samples makes the defects visually indistinguishable from the normal condition except for the error 3 (peening), an MLP model is able to recognize them almost as accurately as for non–lubricated samples where only the error 4 (scratching) is visually indistinguishable from the normal condition.

5 Conclusion

This paper investigates the application of neural networks to the recognition of lubrication defects typical to an industrial cold forging process employed by fastener manufacturers. Four types of lubrication errors, typical to production of fasteners, were introduced to a set of sample rods, which were subsequently drawn under laboratory conditions. The drawing force was measured, from which a limited set of features were extracted. The neural network based model learned from these features is able to recognize all types of lubrication errors to a high accuracy. The overall accuracy of the neural network model is around 98% with almost uniform distribution of errors between all four errors and the normal condition. Work is currently in progress to apply the model learned from the laboratory rod samples to production data.

6 Acknowledgements

The authors wish to thank John Vella for the preparation of test samples and data acquisition and Scott Savage for the design and development of a test rig.

References

[1] Breiman L., Friedman J. H., Olshen R. A., and Stone C. J., *Classification and regression trees*, Wansworth and Brooks, Belmont, CA, 1984.

[2] Savage, S. C., Kershaw, D. I. and Hodgson P.D., "Lubrication coating evaluation technique for a cold heading operation". *Proceedings of the IMEA Tooling 99 Conference*, pp. 55–60, 1999.

[3] Frayman Y., Ting K. M. and Wang L., "A fuzzy neural network for datamining: dealing with the problem of small disjuncts," *Proceedings of the International Joint Conference on Neural Networks (IJCNN'99)*, vol. 4, pp. 2490–2493, 1999.

[4] Ripley B. D., *Pattern recognition and neural networks*, Cambridge University Press, 1996.

[5] Weiss, G. M. and Hirsh, H. A, "Quantitative study of small disjuncts", *Proceedings of the Seventeenth National Conference on Artificial Intelligence (AAAI-2000)*, AAAI Press/MIT Press., 2000.