Using artificial neural networks to model aluminium based sheet forming processes and tools details

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Abstract. In this paper, a methodology and a software system will be presented concerning the use of Artificial Neural Networks (ANNs) for modeling aluminium based sheet forming processes. ANNs models’ creation is based on the training of the ANNs using experimental, trial and historical data records of processes’ inputs and outputs. ANNs models are useful in cases that processes’ mathematical models are not accurate enough, are not well defined or are missing e.g. in cases of complex product shapes, new material alloys, new process requirements, micro-scale products, etc. Usually, after the design and modeling of the forming tools (die, punch, etc.) and before mass production, a set of trials takes place at the shop floor for finalizing processes and tools details concerning e.g. tools’ minimum radii, die/punch clearance, press speed, process temperature, etc. and in relation with the material type, the sheet thickness and the quality achieved from the trials. Using data from the shop floor trials and forming theory data, ANNs models can be trained and created, and can be used to estimate processes and tools final details, hence supporting efficient set-up of processes and tools before mass production starts. The proposed ANNs methodology and the respective software system are implemented within the EU H2020 project LoCoMaTech for the aluminium-based sheet forming process HFQ (solution Heat treatment, cold die Forming and Quenching).

1. Introduction
In this paper, a modeling methodology based on Artificial Neural Networks (ANNs) is presented, which supports modeling of metal-based sheet forming processes combined with geometry details of forming tools. Also, the respective ANNs modeling software developed by ANTER Ltd., its performance and modeling accuracy will be presented through 2 application modeling examples concerning aluminium-based sheet forming processes. Besides data concerning certain process parameters (e.g. press speed, etc.), also material properties’ data were used, such as materials’ UTS (Upper Tensile Strength), which concerned the AA6082-O and AA6082-T4 aluminium alloys.

ANNs, originating as a research field of Artificial Intelligence (AI), constitutes a promising modeling application area for sheet metal forming processes [5, 10, 12], especially in cases that existing mathematical models are not accurate enough, are not applicable or are missing. This situation is found in many forming manufacturing problems where experience, extensive set of trials and experimental historical data, combined also with forming theory and Finite Element (FE) simulation results [7] are used for the set-up of a forming process and tooling system. In such cases the use of ANNs can be very useful. ANNs models can be created and trained using historical and/or experimental data sets of records of model’s inputs and outputs. After the training of the ANNs and the creation of the process model, ANNs can be used to estimate process model outputs values for new process inputs. This approach is
very useful for manufacturing applications, especially in cases of: new and complex processes, micro and nano scale processes [2, 9], complex and non-symmetrical product shapes, and when the accurate mathematical modeling of the process is not satisfactory and the final process set-up is achieved after extensive shop-floor trials and quality control checks before mass production is applied.

In figure 1 the ANNs architecture used for creating the sheet forming processes models is given. It is based on the feed-forward Multilayer Perceptron (MLP) Neural Network [3, 4, 8, 11] using 1 input layer with R inputs, 2 hidden layers with S1 and S2 hidden neurons respectively, and 1 output layer with S3 outputs. The training algorithm, which was used, was the back-propagation algorithm [3, 11].

For the specific ANN architecture, the transfer function applied for the 1st and the 2nd hidden layer was the Hyperbolic Tangent Sigmoid function and for the output layer was the linear function. More specifically:

\[ f_1(x) = \frac{e^{s_1-x} - e^{-s_1}}{e^{s_1} + e^{-s_1}} \]
\[ f_2(x) = \frac{e^{s_2-x} - e^{-s_2}}{e^{s_2} + e^{-s_2}} \]
\[ f_3(x) = x \]

2. Application cases
The proposed ANNs modeling method was implemented as a software system developed by ANTER Ltd. and by using this software the user can train process models utilizing data from other similar successful process set-up trials, sheet metal forming theory [1, 6] and shop-floor experts’ knowledge concerning for example the type of the aluminium alloy, the sheet thickness, the speed of the press, geometrical details of the tools (e.g. minimum die radii), etc.

The training procedure for the ANNs models and the performance of the method, in relation with the modeling accuracy results, will be shown through 2 application case examples concerning Aluminium-based sheet forming processes based on the method HFQ (solution Heat treatment, cold die Forming and Quenching), where HFQ is a registered trademark owned by Impression Technologies Ltd. HFQ process includes the following main steps: (a) Heating of an Al-Alloy sheet blank to the required Solution Heat Treatment temperature, (b) Transfer of the heated blank to a press for stamping and (c) Holding of the formed part in the water-cooled tool for quenching. The HFQ process was developed in the Metal Forming and Materials Modeling Group of Imperial College of London led by Professor Jianguo Lin and the relevant patent was transferred to the UK based company Impression Technologies Ltd.
2.1. 1st Application case example
The 1st case example being presented in this section is a process model with 6 inputs and 1 output. The 6 model inputs are: The Upper Tensile Strength (UTS) of the Aluminium Alloy (MPa), the sheet thickness (mm), the Solution Heat Treatment (SHT) Temperature (°C), the SHT time (min), the press speed (m/min) and the clearance between the die and the punch (mm). The output of the model is the minimum radius R of the die top corner in mm (see figure 2).

![Die Top Radius R](image)

**Figure 2.** Process model with 6 Inputs – 1 Output.

After defining the inputs and the output of the model, the next step concerned the selection of the number of neurons of the 1st and the 2nd hidden layers, which were estimated during the training of the ANN and were adjusted through a test and trial procedure in an effort to minimize the training error for the output of the model. For the specific ANN process model, a 6-18-6-1 architecture was applied with 18 neurons in the 1st hidden layer and 6 neurons in the 2nd hidden layer respectively. After several trials and 1000 training iterations, the Mean Absolute Error (MAE) for the model’s output was MAE=0.01001 mm and when expressed as percentage Mean Absolute Error (MAE %) was 0.17951 %, which means that the ANN was capable to learn and create the process model with satisfactory accuracy for the specific process. The training data set, which was used, consisted of 100 records of model’s inputs and output values. The following figure 3 gives a view of the convergence steps of the training, showing how the ANN behaves in comparison with the physical model after 10, 100 and 1000 training iterations and with a learning rate of 0.005. In the 3 diagrams of figure 3 the straight lines represent the physical model’s output target values for the 100 training data records, and the non-straight lines represent the respective ANN’s output results for the same inputs after 10, 100 and 1000 training iterations respectively. These 3 diagrams show how the ANN model gradually converges to the physical model, and also give a view of the convergence accuracy after the 1000 training iterations, when the two lines become almost identical (MAE = 0.01001 mm for the model output). For the analytical definition and calculations of the MAE please see the explanation notes of table 1.
Figure 3. Training convergence and model approximation after 10, 100 and 1000 training iterations respectively.
2.2. 2nd Application case example

This 2nd application case example concerns a more complex process model consisting of 3 inputs and 4 outputs. The 3 model inputs are: The Upper Tensile Strength (UTS) of the Aluminium Alloy (MPa), the sheet thickness (mm) and the needed minimum radius $R$ (mm) of the die top corner. The 4 model outputs are: the Solution Heat Treatment (SHT) Temperature ($^\circ$C), the SHT time (min), the press speed (m/min) and the clearance between the die and the punch (mm). The ANN architecture chosen was a 3-12-12-4 feed-forward MLP ANN that included 12 neurons in the 1st hidden layer and 12 neurons in the 2nd hidden layer. All the rest characteristics of the ANN e.g. transfer functions, training algorithm, learning rate, training data set, etc. were the same as those of the 1st application case example, which have been already described in the previous sections of the paper. The possibility for calculating 4 output values of the model, increases its complexity, but it also makes the model more powerful and capable to calculate 4 answer values when only 3 inputs values are provided by the user (Figure 4).

After 5000 training iterations, the ANN model converged satisfactorily to the physical model with Mean Absolute Errors (MAEs %) less than 0.6% for all the 4 model outputs (see table 1). Figure 5 gives a view of the convergence steps of the training, showing how the ANN model behaves after 10, 500 and 5000 training iterations respectively and how it approximates the physical model target values for the 4th output of the model, which is the Clearance in mm between the die and the punch. In a similar manner, the ANN model behaves and approximates the physical model target values for the rest 3 outputs also with very small training MAEs. In table 1 the Mean Absolute Errors (MAEs) achieved, after several trials and 5000 training iterations, for all the 4 process output parameters are given:

![Figure 4. The 3 Inputs and the 4 Outputs of the 3-12-12-4 ANN process model.](image)

| Output No | Process Parameters (Process Outputs) | Units       | MAE$^a$ | MAE(%)$^b$ |
|-----------|-------------------------------------|-------------|---------|-----------|
| 1         | Solution Heat Treatment (SHT)       | °C          | 0.05701 | 0.01097   |
| 2         | SHT time                            | min         | 0.00116 | 0.08354   |
| 3         | Press speed                         | m/min       | 0.04286 | 0.22987   |
| 4         | Clearance between die and punch     | mm          | 0.00980 | 0.51156   |

where:

$^a \text{MAE}_i = \frac{\sum_{j=1}^{n}|T_{ij} - A_{ij}|}{n}$

$^b \text{MAE}_i \% = \frac{\sum_{j=1}^{n}|T_{ij} - A_{ij}|}{T_{ij}} \times 100$

- $\text{MAE}_i$ is the Mean Absolute Error of the $i$ model output achieved after a certain number of training iterations and $\text{MAE}_i \%$ is the percentage Mean Absolute Error of the $i$ model output.
- $n$ is the size of the training data set (number of training records consisting of the inputs and the outputs of the model).
- $j$ is the number of the training data record ($j= 1, \ldots, n$).
- $T_{ij}$ is the existing physical model target value of the $i$ model output of the $j$ training data record.
- $A_{ij}$ is the calculation result from the ANN, after its training, for the $i$ model output of the $j$ training data record.
Figure 5. Training convergence and model approximation for the 4th output of the model after 10, 500 and 5000 training iterations respectively.
3. Conclusions
In this paper, an ANNs methodology and the respective software developed for modeling aluminium-based sheet forming processes were presented, together with the modeling accuracy achieved in 2 implementation case study examples. It was shown that even in the multi-input and multi-output process model, which was the 2nd case example with the 3 inputs and the 4 outputs, the modeling accuracy was satisfactory and the convergence of the respective ANN model to the physical model was successful after 5000 of training iterations applied to the specific ANN architecture. This ANN modeling software system was implemented as a Web application and was developed by ANTER Ltd. using the .NET programming environment of Visual Studio 2013 and more specifically the programming languages C#, ASP.NET and the MS-SQL Database System. For both the case examples implemented and even though the software was installed in a Web Server and was running as a Web application, the training of the 1-output ANN model lasted 2 minutes and of the 4-output ANN model lasted 20 minutes due its higher complexity, showing that the training duration was adequately efficient in both cases. After the training, the system was able to calculate and return the results from the trained ANNs in almost real time or the latest in a few seconds depending on the internet connection speed and the user’s machine (PC, smartphone, etc.). Additionally, it should be mentioned that the proposed ANNs methodology can be used both as a standalone process modeling tool and as a supplement to Finite Element Modeling (FEM) simulation results e.g. for estimations of the final tools’ geometry details in relation with process conditions and parameters before the final process set-up. The proposed ANNs modeling methodology and the software system can also be applied in a similar manner for other types of materials (e.g. steel).

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References
[1] Boljanovic V 2004 Sheet Metal Forming Processes and Die Design (New York: Industrial Press) pp 69-83
[2] Chronakis I S, Mekras N D, Wiesauer K, Breuer E, Stifter D, Fuentes G F and Qin Yi 2009 MASMICRO micro-/nano-materials processing, analysis, inspection and materials knowledge management International Journal of Advanced Manufacturing Technology 47 963-71
[3] Hagan M T, Demuth H B and Beale M 1995 Neural Network Design (Boston: PWS Publishing Co) pp 11.1-11.23
[4] Kasabov N 1996 Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering (Massachusetts: MIT Press) pp 267-82
[5] Kashid S and Kumar S 2012 Applications of artificial neural networks to sheet metal work – a review American Journal of Intelligent Systems 2 168-76
[6] Kazanowski P 2006 Forming of Aluminum Alloys ASM Handbook - Metalworking: Sheet Forming (OHIO: ASM International) 14B pp 583-99
[7] Kim D j and Kim B M 1998 Application of neural network and FEM for metal forming processes Intern. Journal of Machine Tools and Manufacture 40 911-25
[8] Liao T W and Chen L J 1998 Manufacturing process modeling and optimization based on multi-layer perceptron network J. Manuf. Sci. Eng. 120 109-19
[9] Mekras N and Artemankis A 2012 Using artificial neural networks to model extrusion processes for the manufacturing of polymeric micro-tubes IOP Conf. Series: Materials Science and Engineering 40 (2012) 012041
[10] Nahak B, Bhardwaj T and Chauhan P S 2014 Development and modelling of hydro-formed circular sheet using neural networks International Journal of Engineering Research 3 230-4
[11] Swingler K 1996 Applying Neural Networks (London: Academic Press Ltd) pp 10-20
[12] Vahdati M, Sedighi M and Mahdavinejad R 2014 Prediction of applied forces in incremental sheet metal forming (ISMF) process by means of artificial neural network (ANN) Journal of Automotive and Applied Mechanics 2 2