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MODELLING OF AIR BENDING USING NEURAL NETWORKS

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Abstract. The main problem considered in this work is the development of a method capable of establishing the required punch displacement to obtain a given forming angle, in Press Brake bending. Current solutions can be based on analytical methods derived from geometrical formulations and additional correction factors [1-3]. These methods provide a quick solution but its applicability can be limited, especially if localized deformation is to be considered. Numerical simulation is increasingly been used and provides accurate results, accordingly to the models used [2]. However the time frame for a solution to be obtained can be a limiting factor. An alternative heuristic method, based on the use of artificial neural networks (NN), is presented in this work. The main justification for this approach lies on the inherent capability of NN to map nonlinear functions [4, 5] and generalization. The experiments were based on data obtained from numerical simulation of the forming process using different sheet metal thicknesses and tool geometries. The results obtained show that NN can provide a better approximation of the function relating the forming angle with the punch displacement.

1 INTRODUCTION

Sheet metal bending is used in a wide range of applications and can be considered an efficient manufacturing process to obtain a variety of components, in which the bends provide additional stiffness and rigidity to the parts..

Air bending assumes a particular role within these processes as the use of the same tools, for a wider range of bending angles, favours higher levels of flexibility and lower batch sizes. However, obtaining a bending angle within the desired level of accuracy can become a limitation in this process, due to its dependence on a variety of parameters such as material properties, sheet metal sizes, tool geometries and process parameters.

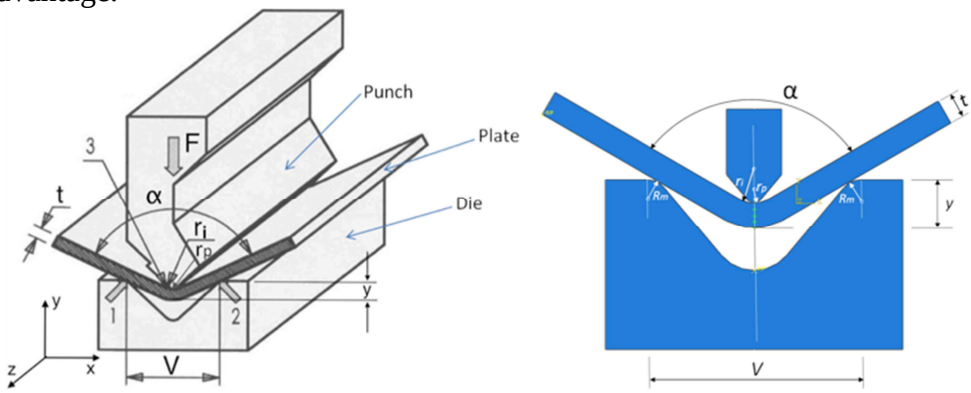
The relationships among these parameters include nonlinear behaviours which makes the development of analytical models more difficult. Artificial neural networks (NN) can be considered as being specially suited to model nonlinear relations and therefore seemed a natural alternative to improve over more conventional approaches. A requirement for using NN is the availability of data, which in our case was obtained through numerical simulation of the bending process with the objective of predicting the punch displacement to obtain a

defined bending angle, not only for recommended V/t relations but also for values outside such recommended range.

In the following sections we describe the basic parameters of air bending, the general approach followed to derive a NN solution, the results obtained and the conclusions of the presented work.

2 AIR BENDING

Air bending can be described as a sheet metal bending process where a punch tool displacement forces the sheet metal along into a die with a "V" shape, as represented in Fig. 2. The objective is not to force the punch all the way into the die, but rather to limit its penetration (y_p) to a value which corresponds to the desired bending angle (α). In this way it is possible to keep the same tools (punch and die) for a variety of bending angles. Knowing the function which relates a desired bending angle (α) with the correct punch displacement (y_p), then becomes a major process requirement. Taking into account the capabilities of modern machine controller's the potential for being included in the machine controller can be a further advantage.



(a) (b)

Figure 1: Air bending process parameters (V, r_i, r_p, y_p, α, t, material) (a) 3D representation; (b) 2D model.

Analytical models are mainly based on the relations that can be derived based on the geometries of the tools, i.e. die opening, V, punch and die radius, r_p and R_m as well as inside natural radius of bending plate, r_i.

The analytical model to be used is the one proposed by J. Bessa Pacheco [2] incorporating die radius (R_m), besides sheet thickness (t), inside natural radius (r_i) and bending angle (α), having the following form:

$$y = \frac{V}{2*\tan(\frac{\alpha}{2})} - (r_i + t + R_m) * \frac{1 - \sin(\frac{\alpha}{2})}{\sin(\frac{\alpha}{2})} \quad (1)$$

However the solutions obtained following these approaches may fail to adequately account for the localised deformations that occur at the contact zones of the sheet metal with the tools (die and punch). These deformations affect the relation between the punch displacement and bending angle, especially when the die opening (V) and sheet metal thickness (t) ratios (V/t) are outside the range of ratios used in industrial practice, between V=6t and V=12t, Fig. 2 [2]. In particular this relation between die opening, *V*, and the thickness, *t*, is defined by:

$$V = k_{vt} * t \tag{2}$$

with k_{vt} varying between six and twelve, as already stated, its value depending also on sheet thickness.

On the other hand the inside radius r_i is given by the die opening, *V*, divided by 6.4, that is:

$$r_i = \frac{V}{6.4} \tag{3}$$

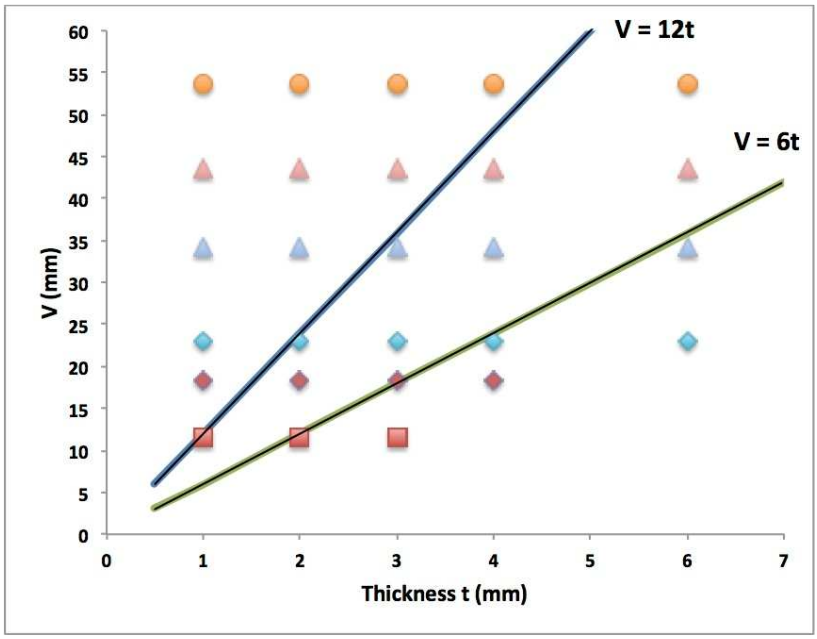


Figure 2: Examples of V, t combinations tested and industrial practice reference rules.

From the simulations of the different (V, t) combinations of Fig. 2, three examples are presented in Figs. 3 to 5, illustrating the effects on contact zones deformations and bending angles of the three areas in Fig. 2: a V/t ratio bellow 6 (see Fig. 3), a V/t ratio within 6 and 12 (see Fig. 4), and a V/t ratio above 12 (see Fig. 5).

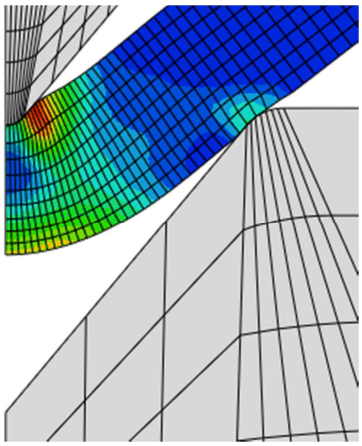


Figure 3: Contact zones effects in a case below V= 6t ratio (V=23mm, t=6mm, V=3.8t).

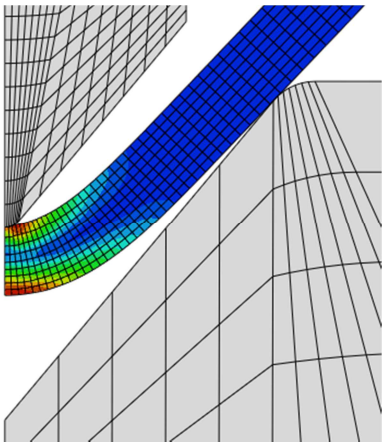


Figure 4: Contact zones effects in a case within V= 12t and V=6t ratios (V=34mm, t=4mm, V=8.5t).

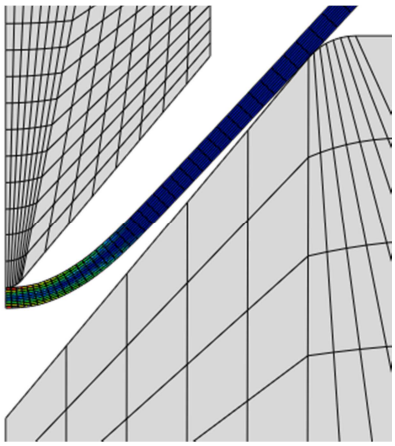


Figure 5: Contact zones effects in a case above the V= 12t ratio (V=34mm, t=1mm, V=34t).

In addition to these nonlinear effects there is also an additional consideration regarding the springback effect [6], that is the difference between the bending angles, under the effect of the punch load and when the load is withdrawn. In the current work we decided to approach the problem separately as we understand there are different nonlinear behaviours in each of these situations and we wanted to deal with them one at a time. Next section describes the proposed approach.

3. PROPOSED APPROACH USING NN

The envisaged approach (Fig. 6) involves taking advantage of different solutions to complement each other's limitations in modelling the air bending process. The idea is to obtain the required punch displacement based on a desired bending angle, material, sheet metal thickness, punch radius and die opening. Analytical solutions provide a directly available, i.e. fast, solution but using a simplified model which does not account for deformation on contact zones and other nonlinear material behaviours. Artificial neural networks (NN) provide a mathematical model which, being based on a large set of parameters, can more easily fit nonlinear mappings of the variables involved. However the development of a NN solution requires the availability of data to properly configure their parameters. The use of numerical simulation (i.e. FEM) provides a greater level of detail in modelling the air bending process but at the expense of greater development times. Nevertheless these time frames are not incompatible with the generation of the required data to develop the NN. If the developed NN generalises adequately, it can be used effectively as a direct solution. Furthermore it does not limit the possibility of being programmed into the controller´s machine.

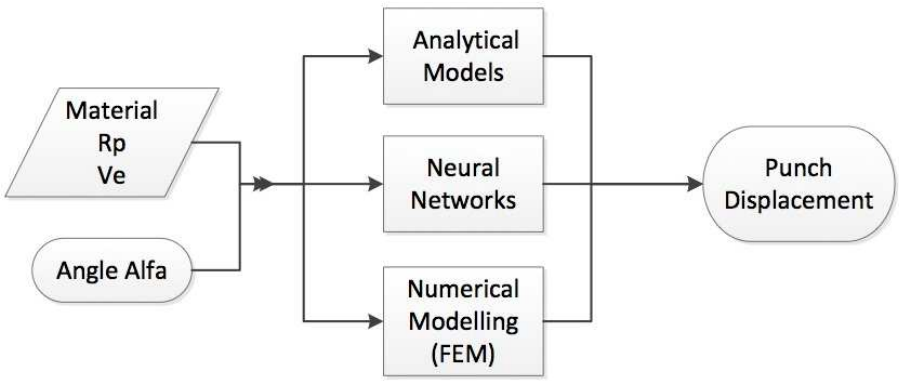


Figure 6: Envisaged approach to model the air bending process (V, r_p, y_p, α, t).

Within this framework we developed a NN to map a function relating the punch displacement (y_p) with three parameters (Fig. 7): sheet metal thickness (t), die opening (V) and desired bending angle (α). In the current work we have used only one type of material, described in a following section, and one punch radius (r_p = 1.0 mm).

3.1 NN approach

Developing a NN solution for a specific problem involves basically selecting a particular type of NN, decide on a representation and coding of the problem into the NN structure, followed by training and testing/validation phases. These are mostly performed iteratively, to set the various design parameters of the specific NN. In this case we select a widely used type of NN structure, the *feedforward backpropagation* type NN and the Levenberg-Marquardt algorithm to minimise the error function. A representation of the problem in the NN structure is based on the information we give the NN and the information we want from the NN which consisted respectively of (V, t, α) as the three inputs and y_p as the NN output, Fig. 7. The number of intermediate, or hidden nodes and the values of the interconnections (weights) between the nodes are design parameters adjusted during the training phases using the data sets available. These data sets consist of instances of the problem, i.e. sets of input values (V, t, α) and respective desired output (y_p^{DES}), in this work obtained by numerical simulation as described in a following section. Once trained, the testing phase compares the results from the NN, i.e. output value (y_p^{NN}) with the desired output values for samples of cases not used during the training phase, giving an indication of the generalization ability of the NN solution developed. The data sets available and the separation in training and testing samples are therefore a key element in designing a NN solution.

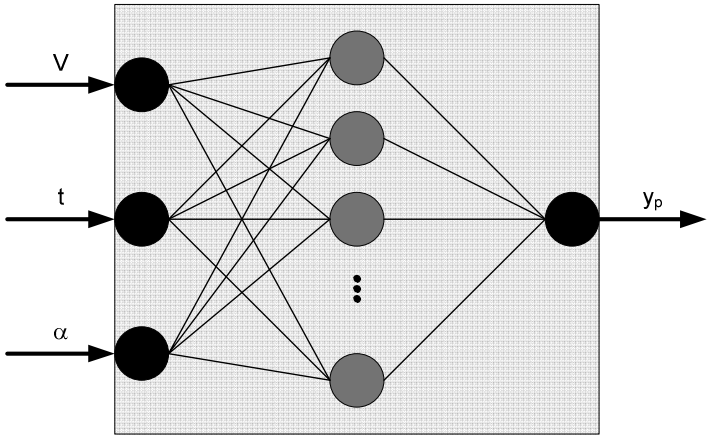


Figure 7: Neural network structure: input (V, t, α) output (y_p), and hidden nodes.

3.2 Data sets used for NN development

The combination of the different cases studied, i.e. V and t, through numerical simulation and used as problem instances in the data sets for the NN development are contained in Table 1. The same material, i.e. mild steel, and a specific punch radius (r_p = 1.0 mm) were considered in those cases. For each of these V and t combinations, 20 simulations of the punch displacement (y_p) and associated bending angle (α) were registered. A total of 660 cases were used. From these, the cases corresponding to V=18.3 and 43.7 were randomly split into a testing set (100) and a validating set (120). The remaining 440 were used as the training set.

Table 1: FEM test combinations and dimensions for the tooling and flange length

$V^{(1)}$ opening [mm]	r_p [mm]	b	R_v	Thickness t [mm]					
				1	1,5	2	3	4	6
11,5	1	15	1	x	x	x	x		
18,3	1	25	1	x	x	x	x	x	
23,1	1	35	1	x	x	x	x	x	x
34,2	1	50	1	x	x	x	x	x	x
43,7	1	50	1	x	x	x	x	x	x
53,7	1	50	1	x	x	x	x	x	x

(1)The V opening, as initial plate support distance, is presented with decimals that corresponds to the round figures (10, 16, 20, 30, 40, 50) usual in bending tooling charaterization, that corresponds to the shape of a machined sharp V prior to grind the die corner radius.

3.3 FEM model and material properties

Figure 8 illustrates the basic FEM model used for the different test combinations summarized in Table 1, showing the relative positions between material and tools. Due to symmetry, only half of the real setup is considered. The plate dimensions and the geometric parameters on the tools, upper punch and lower die, are also summarized in Table 1.

Table 1 shows the test combinations, the characteristics of the material used are compiled in Table 2.

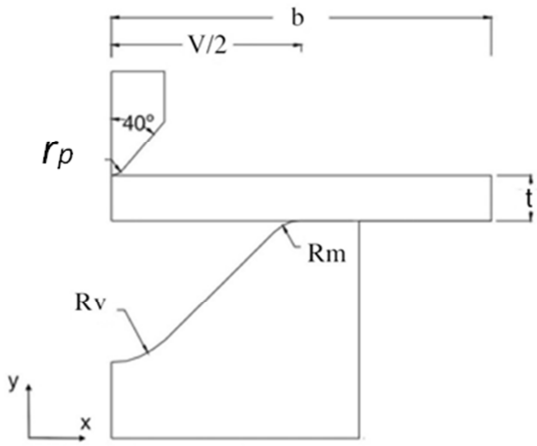


Figure 8– Numerical model used in FEM.

A 2D FEM model was used with sheet, punch and die discretizations by deformable four node solid elements (CPE4R type from ABAQUS® Library).

The bending process was modeled through the dynamic analysis (ABAQUS/Explicit). The sheet plate for all thicknesses was modeled with 450 solid elements and 9 layers, the punch was modeled with 272 solid elements and the die was modeled with a 153 solid elements.

The material which has been used is a mild steel from Posco MS CQ/CR. The steel was characterized according to Swift law and its parameters are presented in Table 2.

Table 2: Mechanical properties of material used.

	Steel MS CQ/CR
Elastic Modulus E [GPa]	210
Poisson coefficient ν	0.3
Proof stress R_{p02} [MPa]	157
Hardening curve σ_Y[MPa]	Swift law $\sigma=k(\varepsilon_0+\varepsilon)^n$
	k = 610
	ε_0 =0.0133
	n=0.3056

3.4 NN training and testing

The error minimisation process during the training phase is illustrated in Fig. 9, where the error function (i.e. Mean Squared Error, MSE (y_p^{DES}- y_p^{NN})) is observed for each of the data sets used (Training, Testing, Validation). The performance on the training set, after each iteration, or epochs, was used to adjust the weights, i.e. connection values linking the NN nodes. The criterion to stop training was based on the error function evolution on the testing set, and the performance on the validation set was used as indication of how unbiased the separation of data in the three data sets has been.

While in Fig. 9 the error function is based on the normalised values associated with the specific representation and coding of the problem into the NN structure, in Table 3 it can be observed the error values over the same sets of data after renormalization of the NN output values (y_p). The high value errors (Error Min and Error Max columns) relative to the rooted MSE column values, refer only to the overall extreme values which occurred, mostly at the initial and end points of the curve as can be visualized for example in Fig. 10 (i.e. V=11.5).

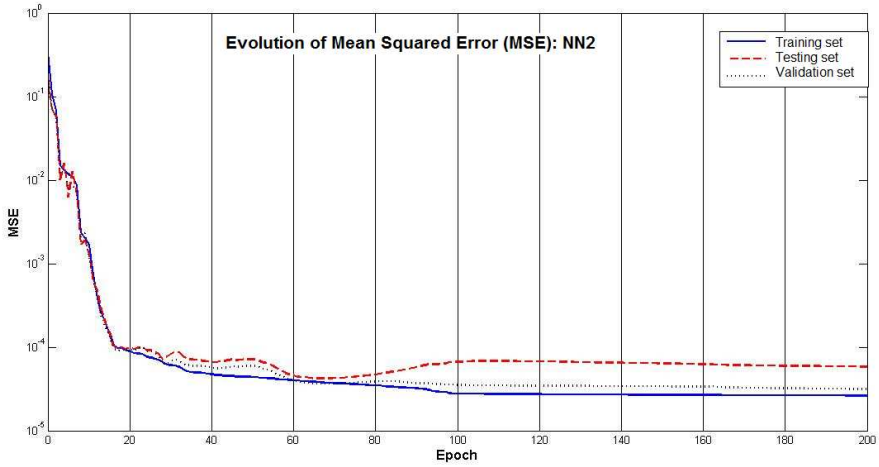


Figure 9: Neural network with 3 inputs (V, t, α) and 1 Output (yp), and two layers of intermediate nodes, each with 4 nodes: performance of MSE error function, normalized values, of training, test, and validation data sets.

Table 3: Comparison of punch displacement (y_p) in [mm], obtained from NN and from numerical simulation (i.e. desired or reference values): extreme values (minimum, maximum) and root squared MSE errors.

Data set	Neural Network 2		
	Error Min.	Error Max.	√(MSE)
Training	-0,2488	0,1853	0,0663
Validation	-0,1537	0,1686	0,0693
Test	-0,1607	0,1505	0,0648

In order to evaluate the performance of the NN against numerical simulation (Target) and the analytical solution ($Y_{analytical}$) solution predicting the punch displacement (y_p) for a specific bending angle, Fig. 10 and Fig. 11 present respectively cases of data used in training and data used in testing, i.e. not “shown” to the NN during training.

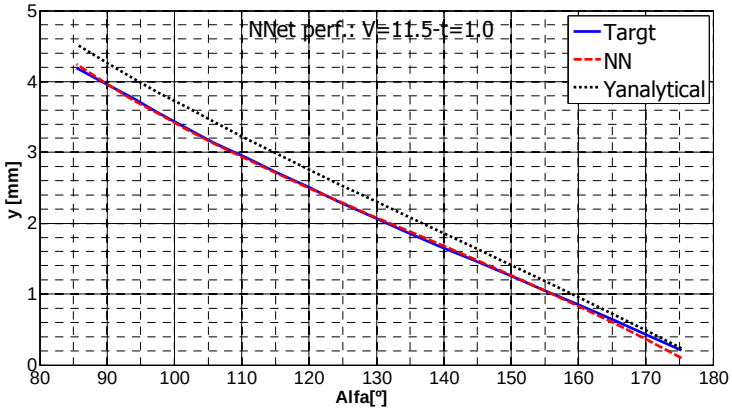


Figure 10: Neural network performance, y_p, against the numerical simulation (Target) and an analytical solution ($y_{analytical}$) in training cases (V=11.5, t=1), i.e. data shown to the NN during training.

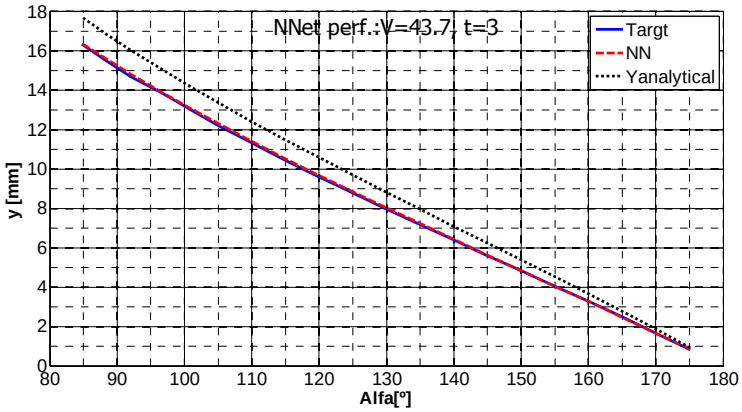


Figure 11: Neural network performance, y_p, against the numerical simulation (Target) and an analytical solution ($y_{analytical}$) in testing cases (V=43.7, t=3), i.e. not shown to the NN during training.

The above representations confirmed the better behaviour of the NN solution comparatively to the analytical one in approximating the target, i.e. the numerical simulation values. In addition it can as well be considered that a good generalization was achieved by the NN solution (i.e. performance on test data).

The following Figures (12-14) illustrate the same behaviour for the three cases showed in section 2 (i.e. V=3.8t, V=8.5t and V=34t).

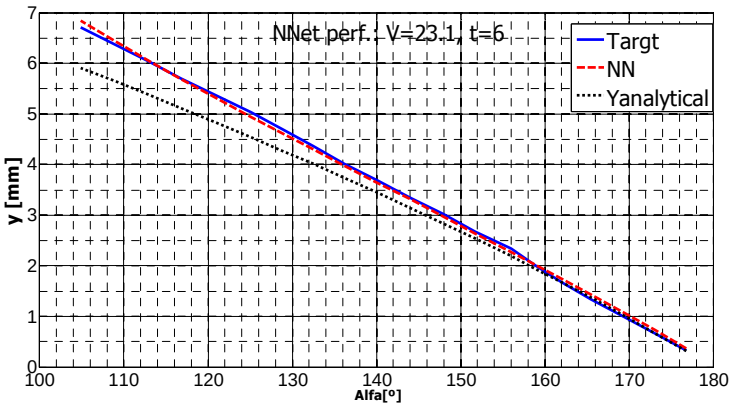


Figure 12: Neural network performance, y_p, against the numerical simulation (Target) and an analytical solution ($y_{analytical}$) in cases with V=3.8t (V=43.7, t=3).

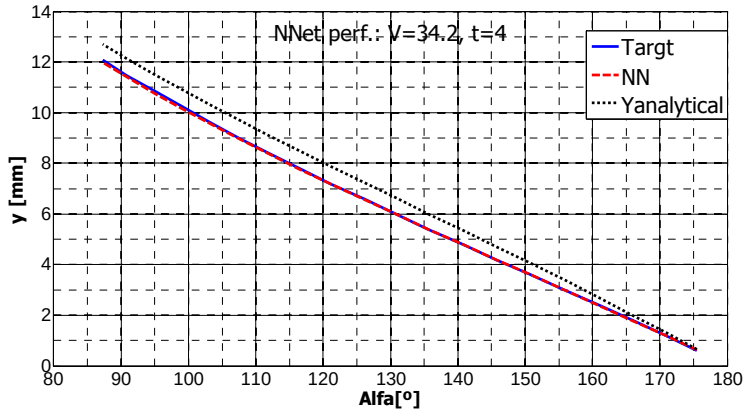


Figure 13: Neural network performance, y_p, against the numerical simulation (Target) and an analytical solution ($y_{analytical}$) in cases with V=8.5t (V=43.7, t=3).

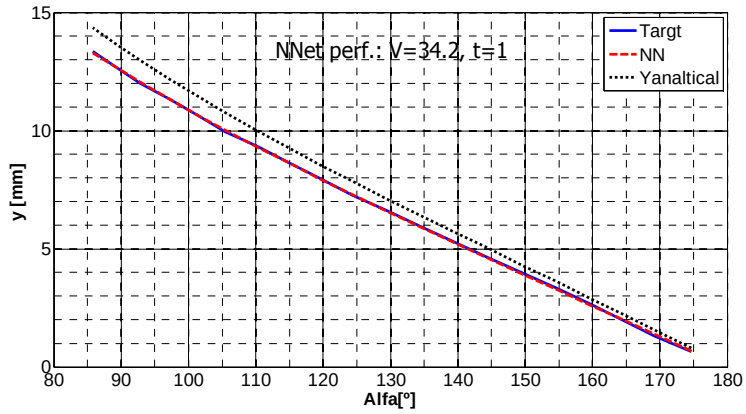


Figure 14: Neural network performance, y_p, against the numerical simulation (Target) and an analytical solution ($y_{analytical}$) in cases with V=34t (V=43.7, t=3).

From the above representations it can also be observed that the NN performs as well inside or outside the V/t zones represented in Fig. 2.

5 CONCLUSIONS

Neural Networks can provide an efficient method to assist the air bending process in the definition of process parameters for press brake bending operations.

It has been shown that Neural Networks provides reliable and accurate results replicating results from bending operations with different variables, e.g. different material thicknesses and different geometry of tools.

Neural Networks can extend the range of current usage of analytic relations by including non-recommended V/t relations, in which local deformation on parts occur (low V/t) or parts in which higher curvature is obtained (high V/t).

Future work will include different materials being incorporated in the analysis as well as integrating the springback behaviour in the prediction of final geometry of the part after being released from tools.

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