Cold Forging Process Planning through Neural Networks

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Introduction

Process planning in multiple-step forging is a critical phase in the production process of cold and hot forged products. The process planner is expected to select the appropriate forming operations and their sequencing (working sequence) to obtain the final product shape in an optimised way. A computer aided approach is highly desirable to reduce the time and cost of the process planning task, particularly in the case of small batch production [1]. In this work, a supervised learning NN approach is utilised for process planning in multiple-step cold forging with the aim to identify the technologically feasible working sequences to be considered for process planning decision making.

Rule-based expert system and training set generation

One of the needs of NN supervised learning is the availability of a training set, made up of known examples, large enough to allow for knowledge acquisition and storage in the NN structure [2]. To build a significantly large training set of multiple-step cold forging operation sequences for the production of multi-diameter shafts, a rule-based expert system was utilised [3]. The expert system took into consideration 4 elementary forming operations (upsetting in 1 step, upsetting in 2 steps, open die forward extrusion, closed die forward extrusion) for the manufacturing of multi-diameter shafts from cylindrical bars (Fig. 1) and the following rules were applied: 1) an element[1] of the workpiece can be upset only if it is joined with an element with a section area higher than the one to upset; 2) upsetting must be carried out before extrusion in order to use simpler dies and avoid higher equipment cost; 3) the same element of the workpiece cannot be extruded more than three times; 4) it is preferable to extrude in the first instance the element with smaller section area (highest reduction first); 5) the reduction in area must be limited (this constraint has a different value for open die and closed die extrusion); 6) if the workpiece has been upset, the subsequent extrusion must be carried out using an open die. The training set for NN learning was built using the working sequences of cold forging operations generated by the rule-based expert system when presented with the following manufacturing task and production conditions: a) work material: low C steel; b) final products: 5-diameter cylindrical shafts with 8 different geometrical configurations; c) for each shaft configuration, 5 different diameters were considered for the initial single-diameter bar; d) the manufacturing of one shaft configuration starting from one initial bar diameter defines one manufacturing "case" (5 manufacturing cases for each shaft configuration: a total of 40 cases); e) to reduce working time, one of the element[1] of the final shaft had the same diameter as the initial bar so that the shaft shape could be achieved with only 4 working steps (at the end of each working step, one element was formed to its final diameter); f) the 4 forming steps in the working sequences were a combination of 4 different elementary operations: upsetting in one step, upsetting in two steps, open die forward extrusion, closed die forward extrusion. Using the above input conditions, 960 working sequences were obtained as output from the expert system. The latter also indicated which of the sequences were technologically feasible and which were not because of the violation of at least one technological rule: 38 sequences were judged acceptable and 922 sequences unacceptable. For each working sequence, the following information details were available: 1) initial diameter of the bar; 2) elementary operation for each of the 4 working steps; 3) element of the workpiece formed during each of the 4 working steps; 4) diameter and length of each element of the workpiece after completion of each working step; 5) if a production rule was violated, which one it was. Some of these information details were provided in alphanumeric format and needed transformation into numeric format through binary coding. The following codes were used: a) type of elementary forming operation (upsetting in one step: 01; upsetting in two steps: 00; forward extrusion in open die: 10; forward extrusion in closed die: 11); b) violation of technological rules (no rule violation, i.e. acceptable sequence: 0; at least one rule violation, i.e. unacceptable sequence: 1). Thus, each working sequence in the training set was represented by a 50-feature pattern vector, coded for NN supervised learning (Fig. 2).

Neural network computation

Three-layer feed-forward back-propagation NNs were considered for parallel data processing [2]. The first 49 features of the working sequence pattern (Fig. 2) were used as

[1] A constant diameter portion in the final shaft shape is defined an "element" of the shaft

input to the NN, whereas the last feature was fed to the output layer of the NN for supervised training through back-propagation of error. Thus, the NN structure was 49-6-1: the input layer had 49 nodes; the hidden layer 6 nodes determined by the "cascade learning" procedure [4]; the output layer only 1 node. The main parameters of the NNs were: a) weights and thresholds randomly initialised between -1 and +1; b) learning coefficient $\eta = 0.3$ for learning rate between input layer and hidden layer and $\eta = 0.15$ for learning rate between hidden and output layer; c) momentum $\alpha = 0.4$; d) learning rules: the Cumulative Delta Rule and the Normal Cumulative Delta Rule; e) transfer functions the sigmoid function and the hyperbolic tangent function; f) the number of learning steps for a complete training set was between 10,000 and 1,000,000; g) epoch size, i.e. the number of training presentations between weight updates, was 6. The NN learning was carried out on an HP-Apollo 9000 with a calculation speed of 60 Mips; maximum processing time was about 1.5 h.

Results and discussion

Three-layer feed-forward back-propagation 49-6-1 NNs were trained under supervised conditions using the training set with the 960 working sequences generated by the expert system: 38 acceptable and 922 unacceptable sequences ("full training set"). The results of the NN computation are shown in Figs. 3 and 4a. The desired NN output is 0 for technologically acceptable sequences and 1 for unacceptable working sequences. The actual NN output is represented by black symbols for acceptable sequences and by white symbols for unacceptable sequences. Actual output values < 0.5 for acceptable sequences and > 0.5 for unacceptable sequences denote correct classifications; otherwise, a misclassification case occurs. A "leave-k-out" approach [5] with k = 1 was also employed: one of the sequences was kept aside in turn while the remaining sequences were used for training. The sequence kept aside was then used for testing and this procedure was repeated for all sequences in the full training set. The results are shown in Figs. 3 and 4b. Fig. 3 shows that the mean value of the NN output for unacceptable sequences is very near the desired value of 1 and the standard deviation is small in both cases of full training set NN learning. As regards acceptable sequences, the NN output mean value is far from the desired value of 0, particularly in the case of "leave-k-out" NN learning with the full training set where a value 0.694 > 0.5 was obtained. Standard deviation is high in both cases of full training set NN learning. A problem encountered in NN training using the full training set is given by the small number of technologically acceptable sequences and the very high number of unacceptable sequences. By examining the full training set, it can be observed that for some manufacturing cases (type B cases) no acceptable working sequence was provided by the expert system. Thus, a "reduced training set" was built by considering, for each of the 8 final product configurations, only the manufacturing cases which contained at least one acceptable sequence (type A cases). The total number of sequences in the reduced training set was 384: 38 acceptable and 346 unacceptable sequences. A 49-6-1 NN was trained and tested using the reduced training set and the results are shown in Figs. 3 and 5a. It can be noted that the number of misclassified cases is decidedly lower than in the case of NN learning with the full training set. The "leave-k-out" approach (k = 1) was utilised also for NN learning with the reduced training set and the results are reported in Figs. 3 and 5b. Fig. 3, shows that the mean value of the NN output for unacceptable sequences is very near the desired value of 1 and the standard deviation is low in both cases of reduced training set NN learning. As regards acceptable sequences, the mean value of the NN output is very near the desired value of 0 in both cases of reduced training set NN learning; it reaches a higher value in the case of the "leave-k-out" method but this value is lower than in both cases of full training set NN learning. Standard deviation, though still high, is lower than in both cases of full training set NN learning.

Future work

Better results are expected if training sets containing higher numbers of acceptable working sequences were available. Training set enrichment (e.g. by relaxing the constraints of the technological rules) based on industrial experience and expert advice in the field of cold forging process design is the aim of the continuation of the present research work.

References

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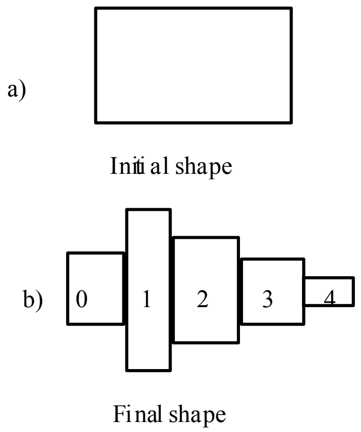

Fig. 1 - (a) Initial shape of the cylindrical bar; (b) final shape of the cylindrical workpiece madeof 5 elements (0, 1, 2, 3, 4) with different diameter.

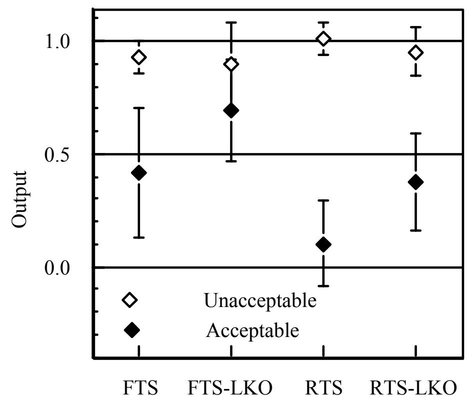

Fig. 3 - Mean and standard deviation of the 49-6-1 NNs output. FTS = full training set; RTS = reduced training set; LKO = "leave-k-out".

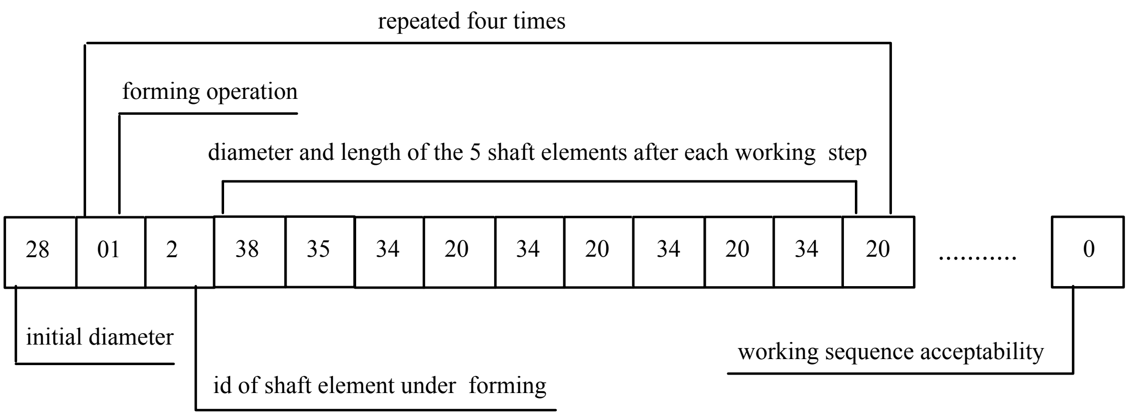

Fig. 2 - 50-feature pattern vector representing a working sequence in the training set.

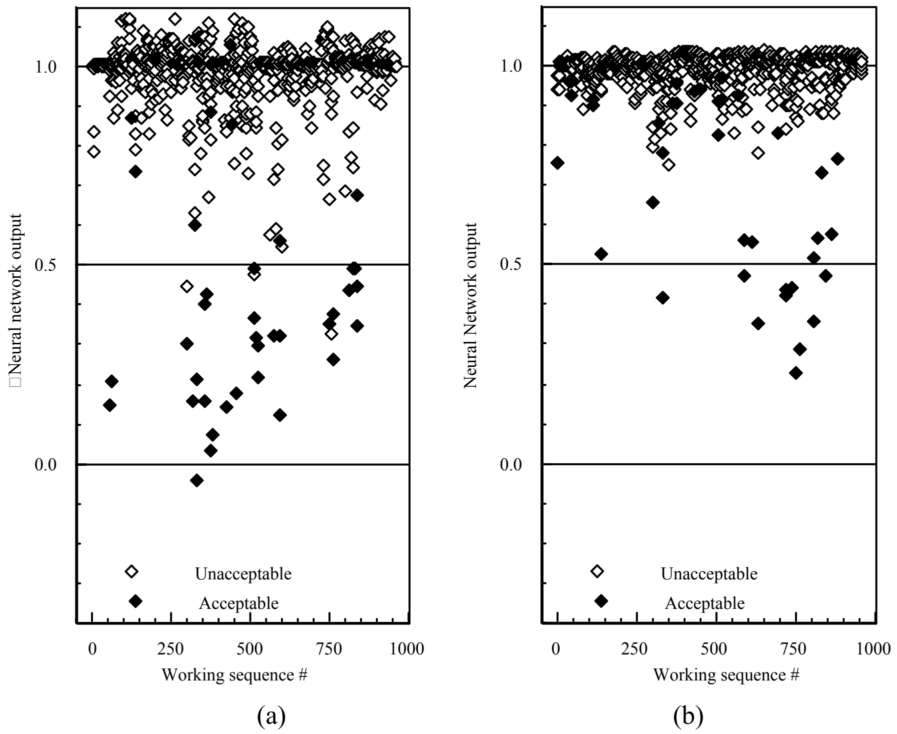

Fig. 4 - Output of the 49-6-1 NN (a) learned with the full training set and (b) using the “leave-k-out” method.

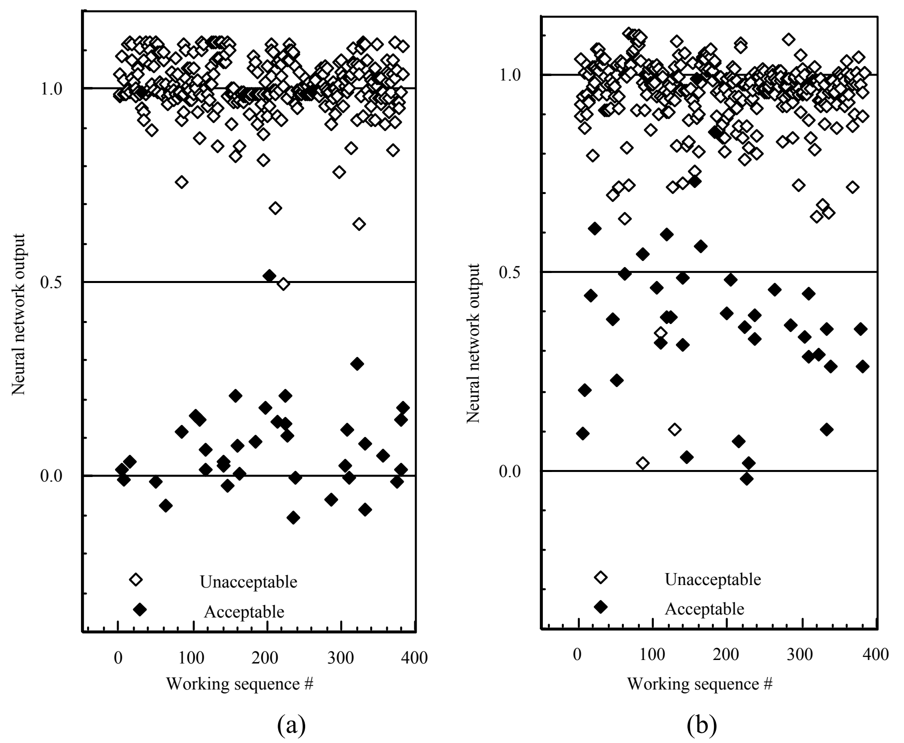

Fig. 5 - Output of the 49-6-1 NN (a) learned with the reduced training set and (b) using the “leave-k-out” method.