Hybrid Integrated System for Air Bending Optimal Design

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***Abstract*— Genetic algorithm (GA) is widely accepted method for handling optimization problems. GA can find optimal solutions for large and irregular search spaces. However, finding optimal solutions using GA is associated with high computational time when coupled with finite element (FE) code, since FE analysis should be applied to each individual of GA populations. A neural network metamodel (NNM) is introduced to reduce the computational time.GA utilizes the NNMas an approximation tool instead of FE. Application examples results show that the metamodelcan be used efficiently to obtainthe optimal process parameters of metal forming operations with large saving in time.**

***IndexTerms*—GA, metamodel, neural networks, springback.**

I. INTRODUCTION

Genetic Algorithm (GA) has been applied to many optimization problems in manufacturing. Richmond and Devenpech used the slip line method to optimize forming energies [1]. Mizugaki et al [2] utilized the GA to find optimal machining time and uncut area of workpiece, Also,Duggirala et al. [3] and Roy et al. [4] applied the GA to find optimal design for drawing and forging processes.

Metamodels are used to reduce the computational time required to evaluate/simulate a problem by approximate the simulation model. A metamodel approximates a multivariate function using sample points selected based on an experimental design.The most well-known metamodels are the response surface methodology [5], Neural network (NN) [6] and Kriging [7,8], a comprehensive review and a comparative study was conducted by Simpson et al. [9].Metamodel can be conducted using the following steps [11]: first, select the type of meta-model; second, run the numerical code for a small number of runs selected based on a predetermined experimental design , and finally, adjust the variables within the metamodel to fit the experimental design runs. Then, themetamodel can be used instead of the simulator. The previous steps can be applied with many options, the results metamodel depend on the choice of these options. For example, if the data is generated by using fractional factorial design and fitting onto a second order polynomial function, then the result metamodelis calledresponse surface, while simulated data may be used to train a neural network withback propagationalgorithm will result in neural network metamodel.

This paper proposes a fast and effective hybridization between the neural network metamodeland GA to find the optimal design of air bending process.

II. NEURAL NETWORK

NNs consist of interconnectedneurons in similar manner as the human brain's neurons [6]. Themost importantproperty of NNs is the ability to learn relationship between input and output data. NNs learn the pattern of the data by repeatedly presenting known input and output data to NN.

The mostwidely employed method for training NNis supervised learning. This method implies that there is prior knowledge of the system to be modeled in the form of input /output pairs. In a feed-forward network the training procedure adjusts the weight of inputs values to produce desired outputs. The error in neurons is calculated as the difference between the NN's output and the desired output. The interconnecting weights then modified to minimize the error at each neuron. Hornik et al. [10]proved that multilayer NNs can be used to approximate any function with acceptable accuracy.

III. GENETIC ALGORITHM

GA [14] is a well-known computationally search method. GA is useful to solve the complex problems where the analytical solutions are difficult to obtain. However, GA needs

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large number of function evaluations. GA represents the individuals in the population as bit strings. Eachindividual, which represent a solution for the problem,consists of a fixed length bit string. The general procedure of GA is shown in Figure 1. GA starts with an initial randomly selected population. The individuals of the initial population are evaluated and their fitness' are measured. Next, GA operations including crossover and mutation, etc. are applied to the current population to generate new population with new generations of individuals. The selection of the individual to next generation is based on its fitness,as the fitness is better as the probability to select that individual is higher. The new generated individuals are evaluated to determine their fitness. The algorithm is continued until the fitness of the best individual in the population reaches a desired fitness.

IV. Result and Discussion

A. The air bending process

Bending process is one of popular manufacturing processes that can be used to produce very small components like small electronic parts, or large products such as parts of vehicle components including body, doors, etc. The accuracy of formed product depends on bending process including the springback. An accurate prediction of springbackis important to determine the punch displacement that is required to achieve a certain bend angle after springback. Many analytical models are available to predict springback[15,16].

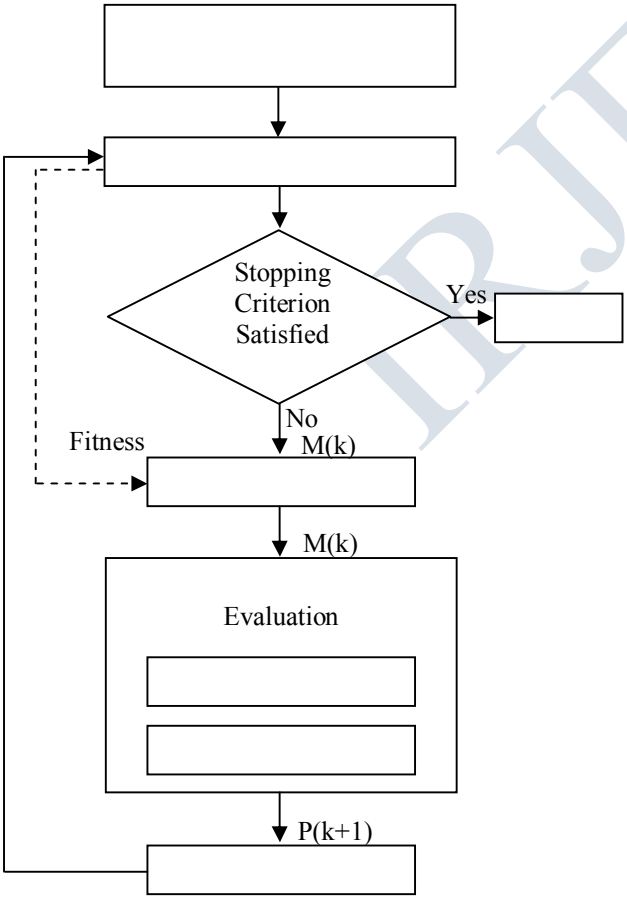


Figure 1 Flow chart for GA

Figure 2 shows the operation of the air-bending process. This process consists of two stages. The first stage is loading stage,in this stage the sheet is bent to take the die shape. During loading stage, the sheet undergoes elastoplastic deformation. The second stage is unloading stage, in this stage the bent sheet is removed. The difference between the bending angle before and after unloading is the springback angle which can be calculated using the following equation:

$$\Delta\theta = \theta_1 - \theta_2 \quad (1)$$

There are many variables affect the value of springback angle. These parameters include material parameters such as Young' modulus E, the yield strength to (σy) , the strength coefficient (k), strain hardening coefficient (n)and geometrical parameterssuch as sheet thickness (t), the punch radius (Rp), die radius (Rd), die width (Wd). A NN developed in this study can be described by the following nonlinear relation:

$$\Delta\theta = f(E, \sigma_y, k, n, t, R_p, R_d, W_d, \theta_1) \quad (2)$$

B. The Finite Element Model

The finite element model for the air bending process is shown in Figure 3, the model has the following assumptions: i) isotropic and homogenous sheet is assumed. ii) FE analysis is simplified to 2D plane strain problem. A four-node quadrilateral plane strain element is used [12].

The implicit model is based on the updated Lagrange formulation which takes into account both material and geometrical non-linearites. The nonlinear FE equations are solved by using full Newton-Rahpson method. The strain hardening is assumed to follows Swift's equation as

$$\bar{\sigma} = k(\varepsilon_0 + \bar{\varepsilon})^n \quad (3)$$

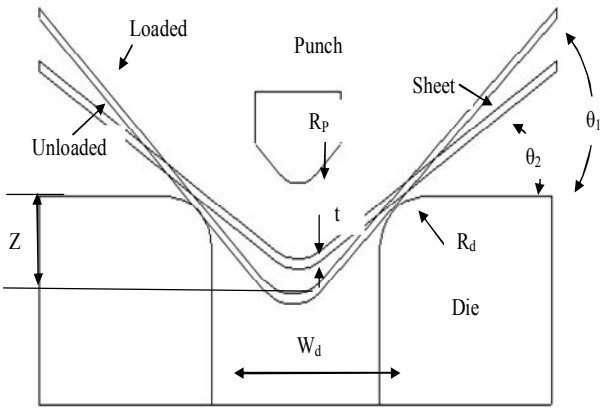


Figure 2 Air bending process

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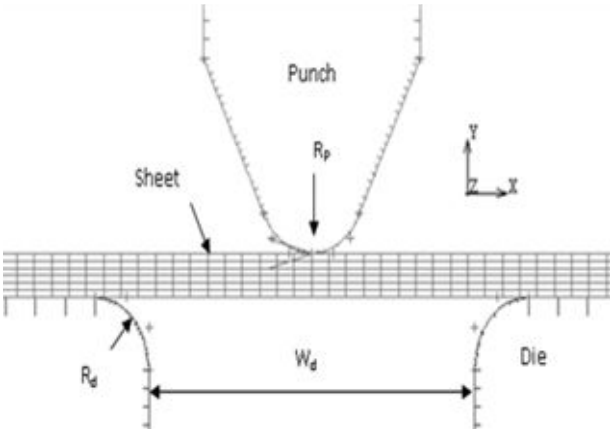


Figure 3 Finite element model for bending

C. Training Examples

A database including the designs and their corresponding performance is needed to train and validate the metamodel. These designs should provide information about the relation between the input and the outputvariables. This allows determiningan accurate neural network metamodel (NNM). In this study, the training examples for the NNM are selected based on D-optimality [5] criterion. 100 examples were chosen by specifying a full quadratic model as required by the D-optimalitycriterion.

V. Development of the Neural Network Metamodel

To achieve a well-trained NNM, inputs and outputs values should be normalized between 0 and 1 or -1 and 1. Furthermore, the training example to NNM should be presented in random order.The structure of NNM used in this study is shown in Figure 4.

To determine the optimal number of hidden neurons, NN was trained with the 100 training examples; the network was then exposed to the remaining 50 examples during the validation procedure. The standard deviation was calculated for the 50 examples not shown to the network. Validation is performed to ensure that the network does not follow the training data too closely. If the network did learn the data too closely, which would occur if a large number of hidden neurons were used, a lower mean square error for the 100 training examples would result, but the network would not be able to adapt to inputs for which it was not trained. The validation process was repeated for different numbers of hidden neurons to determine which network provided the lowest validation standard deviation. Nine hidden neurons were determined to provide optimal results for the metamodels.

VI. Integrated Metamodel Genetic Algorithm Optimization

To find the optimum geometric parameters which reduce springback, optimization problem can be formulated as follows:

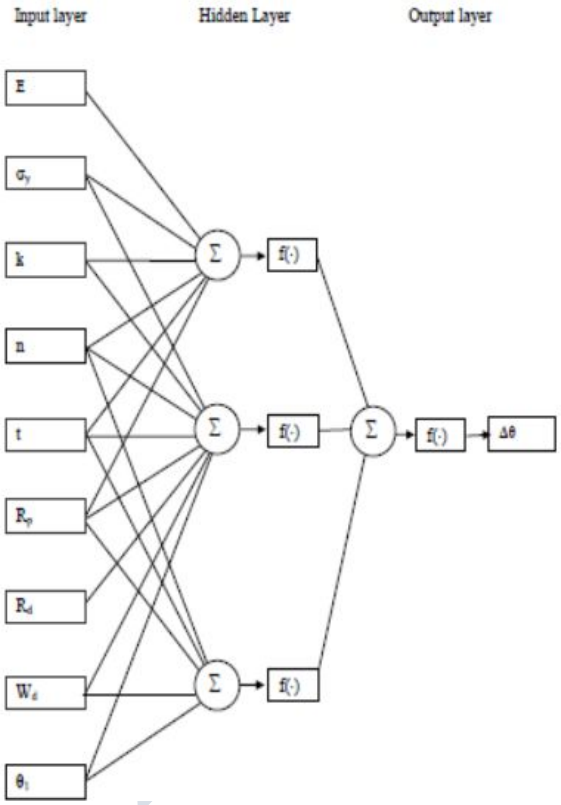


Figure 4 The structure of the NN used in this study

Minimize $f(x_i)$, i =1to *n*

where $f(x_i)$ is the objective or cost function that is to be minimized, x_i =1 to *n* are design variables that are to be optimized. In this problem, the objective function f (x_i) is the springbackvalue $\Delta\theta$. The design variables for the problem are ;Rp , Rd ,and Wd .The constraint on the design variable are $2 \le R_p \le 20$, $2 \le R_d \le 20$ and $40 \le w_d \le 100$.

For solving the above formulated optimization problem the NMM is combined with a GA optimization code as shown in Figure 5.

After initializing the initial population, the springback value is calculated using the neural network metamodel then, the optimization loop of the GA starts until convergence is achieved. During the optimization process, the GA generates the new generation values for the neural network metamodeland obtains the objective function value (springback). Figure 6 shows the evaluation of the cost function with increasing number of generation. From Figure 6, it can be seen that only 29 generation are required to minimize the springback of the initial population from the range shown in Figure 7 to a minimum value of 2 degree springback as shown in Figure 8.

The optimum geometrical parameters obtained at the end of the optimization process are Rp =20 mm, Rd =2, and Wd = 40.This result shows that to achieve a minimum springback in

the air bending process the die width and the die radius must be minimized and the punch radius must be maximized.

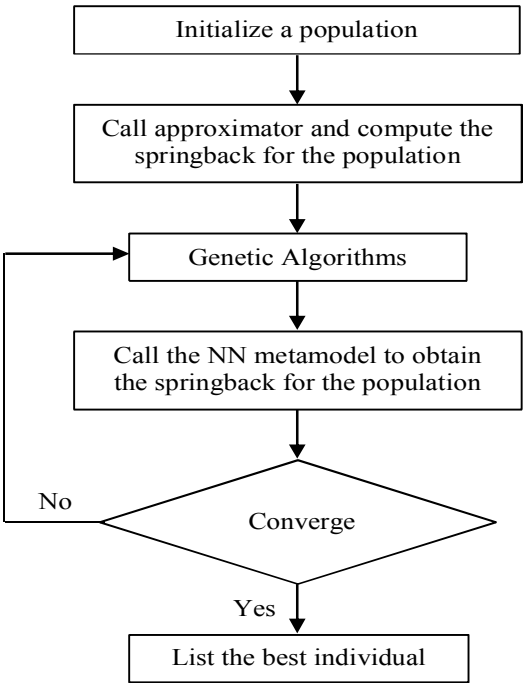


Figure 5 Optimization loop

The computation time for this optimization process was in seconds. The need to run a number of computational expensive

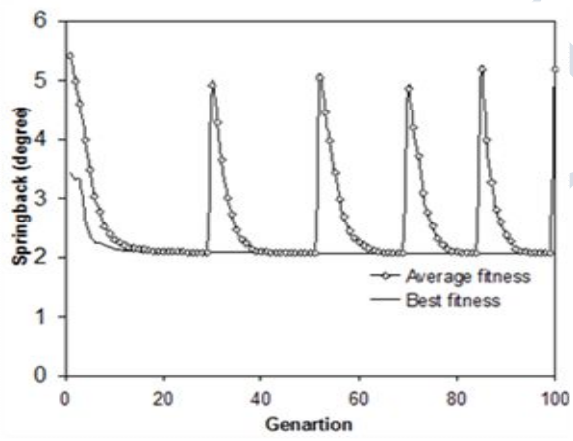


Figure 6 Average and best fitness as function of the generation number

nonlinear finite element models is eliminated, in addition, this optimization method can be used for problems where no existing analytical or numerical solution exist, so that relation between the input and the output parametersof interest can be obtained by training the neural network using training examples obtained from physical experiments.

VII. Conclusions

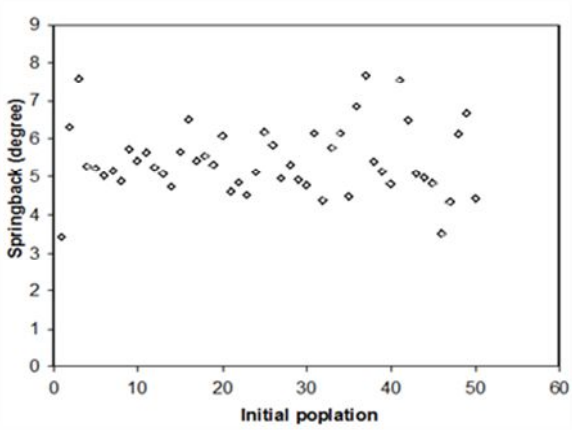


Figure 7 Springback for the initial population

In thispaper,wepresented a method of optimization based

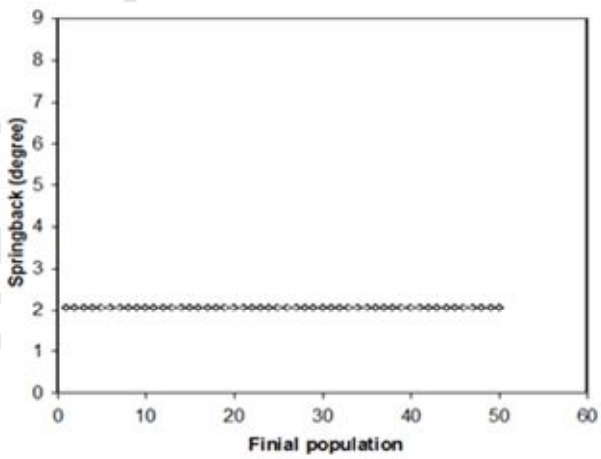


Figure 8 Springback for the final population

on GAs and aNNM. This methodcan be used for optimization problems without explicitly known form of objective functions.Themethods benefits from thegood approximation ability of NN and therobust searching ability of GA to obtain good solutions. The results from the springback problem in the air bending processproved that feasibility and effectiveness of the method.

Acknowledgment

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