MODELIZATION OF IRONING PROCESS. APPLICATION TO A THREE-LAYERED POLYMER COATED STEEL.

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Keywords: Ironing, polymer coated steel, neural network.

Abstract: This document shows a modelization for the ironing process (the most crucial step in can manufacturing) done by using a Neural Network. A design of experiments has been done, in which a number of process variables have been taken in consideration, controlled directly by the operator: die angle, punch speed, temperature and reduction in thickness. These will be the process inputs, whereas the exits are formed by two variables result: Surface quality factor and average roughness. Once the results have been obtained, data have been introduced in a neural network software, so that after being trained the network and used the BP algorithm (BackPropagation), generates a configuration that provides the smaller permissible error. Later, by means of the sensitivity analysis, the neural network generated has been simplified with a new configuration of a minimum error.

1. INTRODUCTION

Beverage cans are no longer simply homes for carbonated soft drinks or beer. Cans are used today for energy drinks, coffee and even wine. One hundred billion beverage cans are produced each year in the United States alone. The economic competitiveness of the industry is fierce and the manufacturing processes involved are extremely reliable. Can makers often calculate the cost of a can to millionths of a cent because of the high production volume. Process modifications which increase or decrease the cost per can even marginally can have a significant impact on the industry.

Essentially all beverage containers in the United States are manufactured from aluminum, whereas beverage cans made in Europe and Asia are approximately 55 percent steel, and 45 percent aluminum alloy. Food containers are still mostly made from steel stock in both Europe and North America.

Modern food and beverage cans are either two- or three-piece construction. The metal forming processes involved in can manufacture are shown in Figure 1. A circular blank is punched from rolled sheet stock, redrawn, ironed in two or three stages, domed, necked, filled and seamed. In between the doming and necking operations, the cans are placed in a wash/coat process which removes the residue lubricants from metal forming (which are invariably toxic in large amounts) and applies a base coating to the metal. The cans are then subjected to one or more spray operations to provide a safe food/drink contact surface and to prevent chemical interactions between container and contents. The polymer also can be applied to the exterior to serve as a permeable coating suitable for further decorating operations. The spray often consists of a polymer resin in a carrier such as methyl ethyl ketone, requiring the carrier fluid to be evaporated, resulting in volatile organic compounds (VOC) which may not be exhausted into the atmosphere but instead must be burned to form more benign products. VOC production is a serious concern of can makers, and has received considerable legislative attention in the past years.

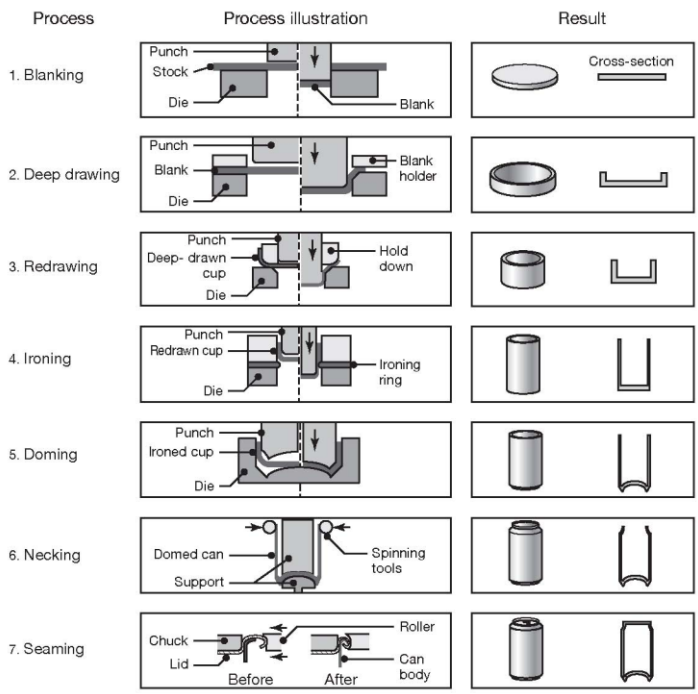

Figure 1: The metal forming steps involved in can manufacture. Source: Kalpakjian and Schmid (2006)

An attractive alternative to the traditional manufacturing process is to use thermoplastic or thermoset laminated rolled steels as base stocks. Such materials consist of pre-heated steel coils that are sandwiched between one or two sheets of polymer. The heated sheets are then immediately quenched, which yields a strong bond between the layers.

It should be noted that the polymers are only useful if they maintain their integrity during forming - any fractures or delamination can cause container corrosion and content spoilage. A cursory review of the metal forming steps in can making results in identification of ironing as the critical operation for polymer coating survivability. In ironing, the pressures are extremely large, the strains and strain rate are very high, and new surface is manufactured from the sheet bulk.

A novel multi-layer polymer coated steel has been developed and is being considered for container applications. This material presents an interesting extension to previous research on polymer laminated steel in ironing, and this paper presents a preliminary evaluation of the new material.

2. EXPERIMENTAL

It has been developed a design of experiments identifying the factors (process variables) that produce changes in the answer variables (result variables).

There are many methods for developing design of experiments as, for instance, factorial designs, fractional factorial designs, regression analysis… It is selected fractional factorial design as the DOE method.

For this design of experiments, we have taken into account the following four variables that are directly controlled in a plastic injection machine (see Table 1).

TABLE 1. Simulator process variables.

Variable	Abbreviation	Units
Temperature	TP	ºC
Die angle	DA	º
Thickness reduction	TR	%
Punch speed	PS	m/s

The most usual models using orthogonal-matrix design is the linear model, based on two levels, and those of second order, based on 3 levels. We will use the last one for the design of experiments, since we want to avoid the disadvantage of using linear expressions that do not allow an accurate adjustment to the real model. Then, the three levels chosen for the mentioned five process variables would be the shown in Table 2.

TABLE 2. Levels of the process variables.

Variable	-1	0	1
Temperature	25	62.5	100
Die angle	2	6	10
Thickness reduction	5	12.5	20
Punch speed	0.5	0.75	1

Then, under the perspective of a factorial design, the total number of tests / simulations to be done would be 35 = 243 tests. As can be seen, it is a high number of tests, but considering Taguchi method, we can reduce significantly the number of tests without having influence on the final result.

3. RESULTS

The Artificial Neural Networks (ANNs) try to be like some basic aspects of the brain, and can be used in a variety of tasks: from simple calculations to help in taking high-level decisions. For this research, ANNs have been chosen because of their good adaptation adjusting non-linear parameters.

The exit variable of a neuron or processing element is not a linear function of the entry variable. Once the network is trained, new entry variables are introduced, and the values are predicted automatically for the respective exit variables.

To obtain the proposed aim, it has been built a neural network using specific software. The training has been done using the Back Propagation algorithm (BP), departing from the random setting of the initial weights between the neurons connections.

The optimal design of a neural network (Figure 2) for the model was obtained after 9145 cycles of training, and consists of an entry layer with four process variables (Table 1), a hidden layer with 10 neurons, another hidden layer with 5 neurons and finally, an exit layer with five variables. The average error is 0.007186.

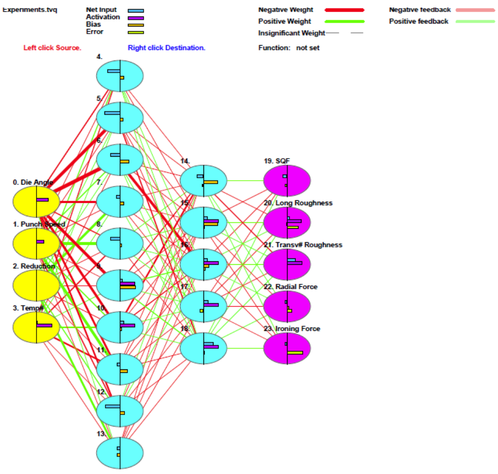

Figure 2. The Neural Network created.

4. CONCLUSIONS

As it can be seen, the precision of the model of neural network is amazing, and perfectly valid. It has been experimentally shown the validity of the model presented in this work and, moreover, it has been obtained using two different methodologies (analysis of sensibility and Pareto's charts), obtaining coincident results for both methods, proving the statements held in this paper.

Column	Input Name	Importance	Relative Importance
0	Die Angle	187.7028	
1	Punch Speed	96.3830	
2	Reduction	93.1122	
3	Temp#	72.6455	

Figure 3. Relative Importance of Input Variables.

Figure 3 shows how important are the input variables. The die angle has revealed as the most important variable and temperature as the less influent one.

Even the described model has been developed using four process variables, it is possible to extend it to the set of process variables that are needed to be considered, though it must be taken into account that the selected variables must be included in the process simulation. With this alternative it is possible to extend the definition of the proposed indicators or include new indicators that have a good adaptation to the effects that are studied.