FEA and Multivariate Statistical Data Analysis of Polypropylene Tube Forming Process

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Abstract. In present, the automotive and aircraft industries, give a lot of attention to plastic materials due to the advantages of light weight, low cost, and extra strength. Although the metal gas forming is a well-known process, the plastic tube forming is a quite new area of research. In this paper, the FEA of the tube forming process of polypropylene tube with different material properties and process parameters and the following multivariate statistical data analysis is presented. The FEA is performed with implementation of axisymmetrical model in Abaqus Explicit. The quality of the final product is introduced as a tube wall thickness distribution along the length of the tube. The product quality dependence on the material properties and process parameters will be illustrated in this research. Also a technique of the optimal tube wall thickness distribution is proposed. This technique allows to adjust the manipulated variables trajectories, such as temperature, strain rate, internal pressure and axial displacement.

INTRODUCTION

Hydroforming and hot gas forming are well-known methods to produce tubular parts with varying cross-sectional areas. Metal tube forming is widely used in automotive and aerospace industry. A technological review of hydroforming process from its early years to very recent dates on various topics such as material, tooling, equipment is summarized in [1].

Recently, a lot of attention has been given to the forming of plastic. The advantages here are numerous due to the properties of plastic, such as lightweight, extra strength and cost-effective material. The most important factors in a tube forming process affecting the quality of the tube are the loading conditions of the process. One of the methods to design the optimal loading curves is introduced in [2].

Another approach for controlling end-product quality properties by adjusting the complete trajectories of the manipulated variables is proposed in this paper. Similar work has been done for an industrial emulsion polymerization process with a condensation polymerization example for the production of nylon [3]. A methodology for finding a window of operating conditions through the model inversion is illustrated in [4]. The concept of analysis and optimization of the final product in the latent variable space of nonlinear PLS models is introduced in [5], [6].

The quality of the produced part is determined by the final shape and uniformity of thickness variation of the tube walls. These objectives can be satisfied by posing the control strategy in the reduced dimensional space of a latent variable model with the following model inversion.

To generate the data, 25 batches with different material properties and process parameters were run. To analyze the autocorrelation and cross-correlation between the input and output process parameters, principal component analysis (PCA) and projection to latent structures (PLS) techniques with the following optimization are employed.

The process was simulated in Abaqus Explicit with 2-D axisymmetrical model. This type of modeling is very common in forming applications. It gives the advantage of fast and fairly accurate representation of the process. The work, showing the numerical simulation of the forming process, is introduced by axisymmetrical model in [7], [8].
PROCESS DESCRIPTION

The process consists of two major phases: the phase of the forming process expansion and the phase of the forming process calibration. In the first phase, the tube is internally pressurized while axially fed towards the expansion zone. In the second phase, the tube is forming the small radii of the die curvature only under internal pressure (Fig 1).


METHODOLOGY

The initial step of the proposing method is input and output parameters determination. Input parameters are presented by material and process variables. To obtain the material parameters data, several tensile test experiments at different temperatures and strain rates were conducted. The temperatures and strain rates used were 100, 130, 140, 150 and 0.1/s, 0.01/s, 0.001/s respectively. The material was cut in the longitudinal direction with dimensions corresponding to those of sample type 4, according to ASTM standards. Tensile test were performed on the Instron testing machine.

Process variables are represented by combination of internal pressure and axial displacement applied during the simulation (Fig 2).

The output parameter is a thickness distribution of the tube walls. This distribution is represented by measured thickness of the tube walls at nine sampling points along the length of the tube. Sampling is conducted at ten even periods of time during the process simulation (Fig 3).

FIGURE 3. Thickness Variation along the Length of the Tube at nine Specific Points.

The paramount goal of DOE and COST approaches is to create representative and informative experiments. COST approach, used in this paper, represents a traditional way of performing experiments. To generate the data, set of simulations included 25 batches with different combination of material and process parameters were run.

Finite Element Modeling of Forming Process

The process is modeled with 2-D axisymmetrical model. Some assumptions are made, such as uniformity of temperature and pressure distribution, isotropic properties of elastic-plastic material, equal displacement of left and right actuators.

The stress-strain curves data for the material input properties were received from the uniaxial tensile tests performed at different temperatures and strain rates.

For the contact formulation, the master-slave approach was used. For the tube modeling, axisymmetrical elements with a reduced integration CAX8R were utilized (Fig 4).

The process parameters, which were implemented in the simulations, were simplified by representing them as a linear ramp function what is not often true in practice. In further research more complex trajectories will be considered.
Multivariate Statistical Data Analysis
(PCA and PLS Methods)

During the process, all process variables trajectories are highly correlated with one another. This implies that their behavior can be represented in a much lower dimensional space using latent variable models based on principal component analysis (PCA) or projection to latent structures (PLS) [9].

Multiway PCA for Batch Trajectory Data

Prior to PCA, data are pre-processed by means of mean centering and scaling to unit variance. By using PCA a data table $X$ is modeled as

$$X = 1^* \bar{x}^T + TP' + E$$

where $1^* \bar{x}^T$ represents the variables averages, $TP'$ models the structure and $E$ is the residual matrix containing the noise.

To understand the forming process in terms of time dependency, the Multi-way PCA for batch trajectory data was performed. The analysis has been done on PCA model with output variables data vs. time. The model was fit with 2 principal components (PC). The loading plot is showing that the first principal component explained the overall thickness variation and the second principal component captured mostly the thickness distribution along the length of tube, especially at the critical points (Fig 5).

FIGURE 5. Loadings for the Output Variables for the Entire Batch

In the plot of mean trajectory of all variables there are three main trends of the output variables distribution. In the beginning of the forming process all output variables have the same values. During the forming process, the variables assigned to the ends of the tube (Y1, Y2, Y8, Y9) are slightly changing, but almost remaining at the same initial values. The variables Y3, Y7 (points at the corner) are changing the direction toward thinning almost at the second step of the process. The variables assigned to the center part of the tube (Y4, Y5, Y6) have the most significant change. The thickness reduction during the process is approximately 0.7 mm (Fig 6).

FIGURE 6. Mean Trajectories for the Thickness Distribution at 9 Sampling Points.

Projection to Latent Structure (PLS)

Linear PLS regression is performed by projecting the scaled data onto lower dimensional subspaces using SimcaP software package. PLS is a regression extension of PCA, which is used to connect the information in two blocks of variables, $X$ and $Y$, to each other. $X$ and $Y$ matrices are input and output data matrices respectively.

$$X = TP^T + E$$
$$Y = TQ^T + F$$

where the columns of $T$ are the values of new latent variables that capture most of the variability in the data, $P$ and $Q$ are the loading matrices for $X$ and $Y$ respectively, and $E$ and $F$ are residual matrices.

The model was fit with three principal components and following values of explained and predicted variables: $R^2_X=0.723$, $R^2_Y=0.935$, $Q^2=0.883$
FIGURE 7. Scores and Loadings Plot for the First Two Principal Components

The first PC captured the overall thickness variation, which mostly depends on the axial displacement applied during the simulation. The second PC captured the effect of strain rate on the thickness variation and it is mostly affecting the critical points of the tube (Fig 7).

FIGURE 8. Scores and Loadings Plot for the Last Two Principal Components

The third PC showed the effect of temperature on the thickness distribution. It has a negative correlation with the critical points of the tube, which means, that with increase of temperature, the critical points become thinner, and positive correlation with remaining points along the length of the tube (Fig 8).

Model Inversion Technique

A feasible set of desired quality characteristics \( Y_{\text{new}}^T \) is related to the process operating conditions with the model

\[
Y_{\text{new}}^T = u_1^T Q^T
\]

The solution through the model inversion provides a single set of process operating conditions \( X_{\text{new}}^T \), which should yield the desired quality characteristics \( Y_{\text{new}}^T \)

\[
X_{\text{new}}^T = Y_{\text{new}}^T (Q^T)^{-1} P^T
\]

The future trajectories are computed through the PLS model with 3 principal components in such a way that their covariance structure is consistent with the past operation. The solution showing the desired thickness distribution vs. deviation from equality is presented in Fig. 9. The smallest deviation from equality at 2.95 mm of all operating points along the length of the tube can be obtained with the desirable value of thickness at 2.7 mm.

FIGURE 9. Desirable Thickness Distribution along the Length of the Tube vs. Deviation from Equality

The thickness distribution along the length of the tube with the desirable thickness at 2.7 mm is illustrated in Fig 10.
FIGURE 10. Optimal Thickness Distribution along the Length of the Tube

The values of manipulated variables trajectories as optimal operating conditions are yielding to the temperature corresponding to the 140.851°C and strain rate at 0.003024/sec. The variables trajectories of the optimal process parameters are illustrated in Fig. 11.

FIGURE 11. Optimal Values of the Process Parameters

CONCLUSIONS

A latent variable method for finding the optimal material properties and process operating conditions has been applied to the tube forming process. Smooth changes in manipulated variable trajectories can be achieved by the model inversion technique. It is expected that increase in the number of input and output data points, time points and making the initial trajectory of the input parameters closer to the real process, will give more accurate and functional results.

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REFERENCES