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Soft modelling of the shaping of metal profiles in rapid tube hydroforming technology

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Abstract

The paper presents an approach to the impact of process parameters in innovative RTH (Rapid Tube Hydroforming) technology for shaping closed metal profiles in flexible and deformable dies. In order to implement the assumed deformation of the deformed profile, the RTH technology requires the monitoring and control of numerous technological parameters, including geometric, material, and technological variables. The paper proposes a two-stage research procedure considering hard modelling (constitutive) and soft modelling (data-driven). Due to the complexity of the technological process, it was required to develop a numerical finite element method FEM model focused on obtaining the adequate profile deformation measured by the ellipsoidality of the cylindrical profile. Based on the results of the numerical experiments, a preliminary soft mathematical model using ANN was developed. Analysing the soft model results, several statistical hypotheses were made and verified to investigate the significance of selected process parameters. Thanks to this, it was possible to select the most important process parameters, i.e., the properties of moulding sands used for RTH dies: the angle of internal friction and cohesion.

Keywords: rapid tube hydroforming RTH, manufacturing, constitutive modelling, soft modelling, finite element method (FEM), artificial neural networks ANN

1. Introduction

The constantly growing requirements and needs to individualise products means that all technologies of rapid prototyping and short series production are dynamically developing. Due to the high costs of die preparation and the time-consuming nature of production start-up, it has not been possible to perform unit or prototype production in the hydroforming technology so far (Sadłowska, 2008). The development of the innovative RTH method, described by Kochański & Sadłowska (2020a, 2020b) and Sadłowska et al. (2020), included hydroforming in the group of technologies allowing manufacturing even in short series. At the same time, the new technology is perfect for manufacturing products from all materials, including AHSS steels that are hard to deform.

The RTH method (from Rapid Tube Hydroforming) consists of shaping a thin-walled closed profile, placed in a die subject to deformation along with the deformation of the profile. This method takes its name (rapid) from the possibility of using it in fields of hydroforming technology unattainable thus far, i.e., for rapid prototyping operations. Classic hydroforming of metal profiles or tubes, widely used in the automotive industry, mainly consists of expanding the profile in a rigid die in order to reflect the shape of the profile after the operation. This approach requires a costly and

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labour-intensive process of designing and producing the die, which means that hydroforming is still mainly used by the richest companies and is primarily used for large-scale and mass production. The RTH method completely changes this approach and is based on the deformation of the profile in the die deforming in a controlled manner along with the profile. The RTH die has such properties since it is made of readily available and cheap materials, similar in properties to moulding sands, it is easy to manufacture and, moreover, it can be recycled. For these features to be met, both the die and the shaped profile must have appropriate material properties, and the process parameters should be selected very carefully. This is due to the synergistic effect of the die and the profile, which interact with each other throughout the entire process, changing their properties at the same time. As for the deformation of metal profiles, it is related to the strengthening of the material, while the RTH die material behaves in a different way than metal. For example, it can undergo local compaction, and in some cases it can also be moved without destructive deformation (Sadłowska et al., 2021). This behaviour is characteristic of grain materials, the behaviour of which is described by the mechanics of granular media.

Therefore, the RTH process, also called the forming method in susceptible dies, must be described with numerous variables that can be conveniently systematised into three groups of process parameters (Fig. 1):

– geometric parameters,
– materials parameters,
– technology parameters.

The group of geometric variables includes the description of the geometry of two areas: a shaped profile and a die. For simple initial shapes of a tube-type profile, the geometry of the profile can be described by three parameters: diameter, length, and wall thickness. The description of the die geometry is more complex because the original (initial) contour of the cavity is related to the properties of the die material, which results from the assumptions of the method itself, (Kochański & Sadłowska, 2020a). The group of material variables collects parameters related to the properties of the profile material, the material used to make the die and the values describing the boundary conditions between the profile and the die or the die and the box, e.g., friction coefficients. The last group of technological variables includes the largest number of parameters relating to the behaviour of the liquid that forms the profile or the state of the machine during the process. Due to the high level of technological advancement of the method, all of the parameters should be monitored.

Moreover, it should be noted that, due to the innovative approach of the method and the limited scope of the research carried out so far, there is no full expert knowledge explaining the significance of the influence of individual variables on the final shape and properties of the product. Therefore, the synergistic influence of many factors in the process is unknown due to the simultaneous interaction of the profile and the die. Due to the low level of development of RTH technology, performing enough experiments to determine the significance of the analysed process parameters is costly and time-consuming, and in many cases, simply unprofitable. Hence, the RTH method was originally developed with the aid of advanced modelling tools, both hard (constitutive) and soft (data-driven). This article presents one of the possible approaches for extending the knowledge of the RTH method.

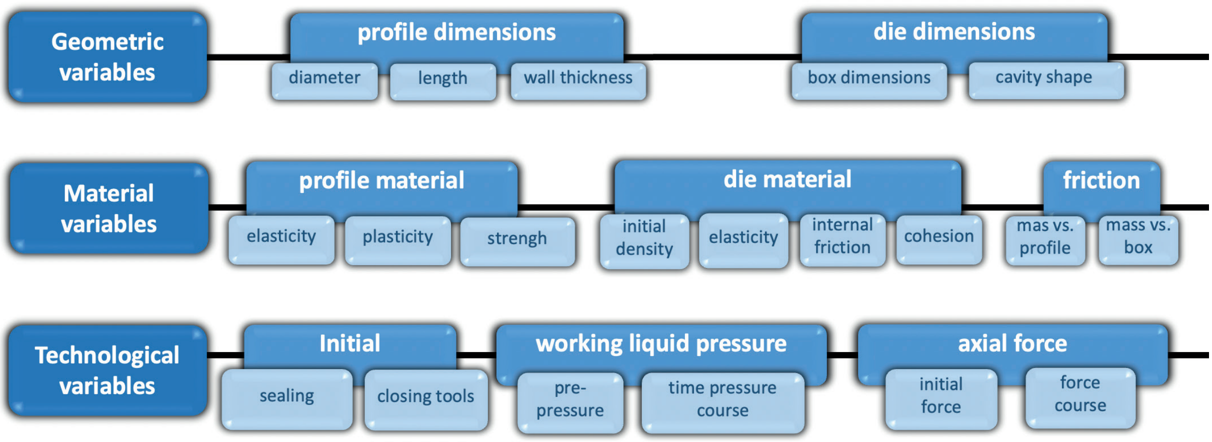


Fig. 1. RTH process variables

2. Methods

In light of the above, a two-stage research approach was proposed at this stage of the examination of a new RTH technology which consisted of:

- The development of a hard mathematical model (constitutive) of the analysed process and performance of bench experiments to verify the built model;
- The development of a soft mathematical model (data driven) using the database obtained in numerical modelling and analysing the obtained mathematical model in terms of the significance of process parameters.

2.1. Hard modelling (constitutive)

The developed two-dimensional finite element method FEM model described by Sadłowska et al. (2020) is based on a selected number of process parameters and includes the profile geometry (diameter and wall thickness), die geometry (dimensions of the cavity and box dimensions), properties of the mass used to make the die (internal friction angle, cohesion coefficient, Young's modulus, Poisson's ratio), profile material properties (Young's modulus, Poisson's ratio, Yield stress, stress-strain curve) and friction coefficients for pairs: profile – die, die – box (Fig. 1).

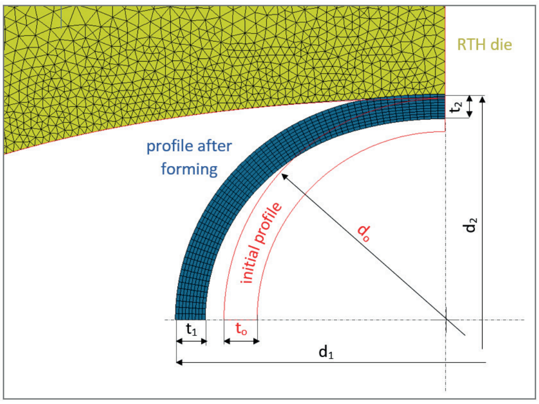


Fig. 2. Geometry of deformed profile

The established numerical model was verified in the testing-bench experiments described by Kochański & Sadłowska (2020b) and Sadłowska et al. (2020). A profile with a circular cross-section was shaped in the susceptible die during experiments to obtain an ellipsoidal cross-section. The research goal was to obtain maximum ellipsoidality defined as the proportion of the ellipse main diameters d_1 and d_2 with a combination of minimal deviation of the wall thickness t_1 and t_2 in the directions determined by the main diameters, as shown in Figure 2.

A series of numerical experiments were performed by means of the verified constitutive numerical FEM model using a wide range of process parameters variability. The following variables were used in numerical modelling: internal friction angle, cohesion coefficient, mass Young's modulus, friction coefficient profile – mass, profile material property index (considering mechanical material properties), and wall thickness. The process parameters and the range of their variability of all parameters are presented in Table 1.

Table 1. The range of variability of parameters used in numerical modelling

Parameter	Range	Units
Internal friction angle φ	10÷50	°
Cohesion coefficient c	0.1÷1.5	MPa
Mould (die) material Young's modulus E	100÷1000	MPa
Profile – die material friction coefficient μ	0.01÷0.1	–
Profile material factor ψ	0.56÷1.0	–
Wall thickness g	1.0÷3.0	mm

The variability distributions of individual parameters are shown in Figure 3. The distribution of the cohesion coefficient variation as a function of the internal friction angle shown in Figure 3a shows an increased number of experiments in the range of the friction angle of 35° and a cohesion coefficient below 1.

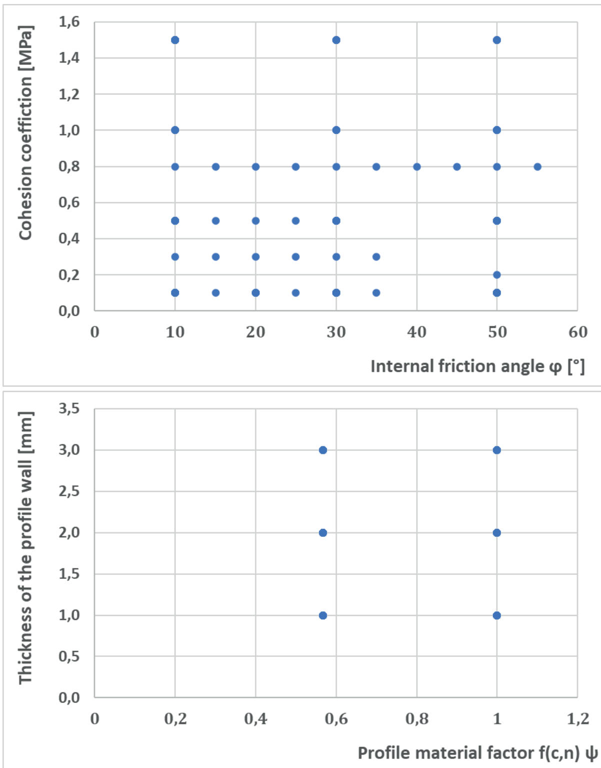


Fig. 3. The variability distributions of individual parameters used in FEM modelling: a) cohesion coefficient vs. internal friction angle; b) wall thickness vs. profile material factor

Earlier work by Sadłowska et al. (2020) showed that this range of variability is easy to obtain in the die material and that within this range of variation, the applied mass changes the nature of its behaviour under a profile shaping load. The distribution of the material factor profile ψ in relation to the profile thickness (see Fig. 3b) adopted in the numerical experiments results from the fact that the numerical studies included profiles made of two steel grades, having different behaviour under load. It was assumed that the material factor profile takes the values 0.56 (for steel R_e = 200 MPa and the stress-strain curve parameters C = 650 MPa and n = 0.25) or 1 (for R_e = 600 MPa, C = 900, n = 0.1). The profiles shaped in the numerical experiments had three wall thicknesses: 1 mm, 2 mm or 3 mm.

2.2. Soft modelling (data-driven)

Soft mathematical modelling was used to develop a predictive model of the variable ellipsoidality which was used in the output layer. The variable ellipsoidality was defined as the proportion of the main diameters of the shaped profile (see Figure 2).

The set of data obtained from numerical modelling was normalised according to the methodology of data preparation presented by Grzegorzewski & Kochanski (2019). This was carried out to avoid the influence of the size of the input variables differed by orders of magnitude.

Afterwards, a soft mathematical model using artificial neural networks was developed for the data from the data set. The neural network used was a three-layer perceptron with one hidden layer. The error back propagation algorithm was used for training. The number of neurons in the input layer was 7, because in addition to the previously mentioned parameters (shown in Table 1), the pressure coefficient of the working liquid was considered. Due to the size of the set of hard numerical modelling results it was decided to use a network with a small number of neurons in the hidden layer in soft modelling. This gives the network a small number of weights to learn. According to suggestion of Pyramid Rule (where a number of hidden neurons equals the square root of the number of input and output neurons product), see Masters (1993) and Rachmatullah et al. (2022), the hidden layer consisted of three neurons. The small number of neurons in the hidden layer means that the neural network has a negligible ability to "remember" all cases in the database. If the observations collected in the database are diverse, then a small neural network has no ability to overfitting. This was important because the aim of the research was to obtain a network with the ability of significant generalisation. The aim of the research was to obtain a tool allowing to determine the qualitative impact of individual parameters on the input variable. One neuron corresponding to the Ellipsoidal value was used in the output layer. A logistic function was used as the activation function in the neurons of the hidden layer. Linear functions were used in the input and output layers. The use of seven neurons in the input layer, three in the hidden layer and one in the output layer resulted in 24 weights to be determined. In combination with the number of 150 observations collected in the database, it guarantees an appropriate proportion, which is usually defined as not less than 4, (Masters, 1993). The Statistica 13.3 package was used to build the neural network model. For the defined connection topology (number of neurons in layers: 7 – 3 – 1), 300 networks were made. The typical division of the database into sets was used: training – 70%, testing – 15% and validating – 15%. Each training was performed on a new, random division of the set. From all nets, the best five were selected. As the final prediction result, average values calculated from five selected networks were used.

Figure 4 shows the values of ellipsoidality determined from FEM modelling and ellipsoidality predictions obtained from the soft ANN model. For predictions made using ANN, the mean square error MSE (for normalised quantities) was 0.005.

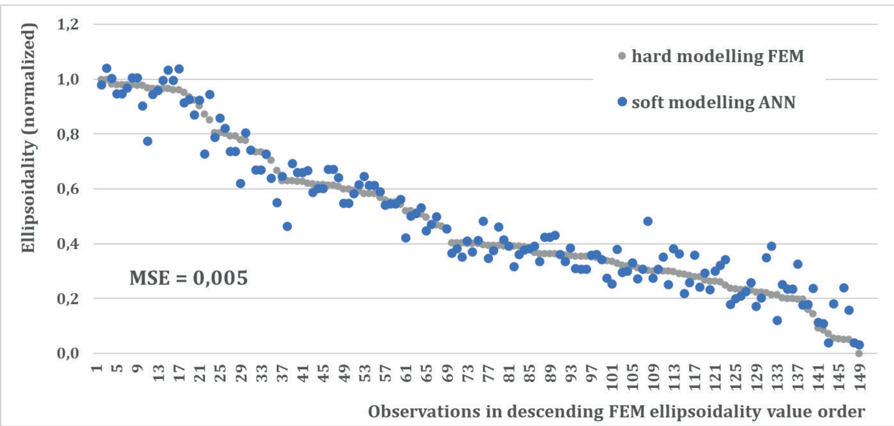
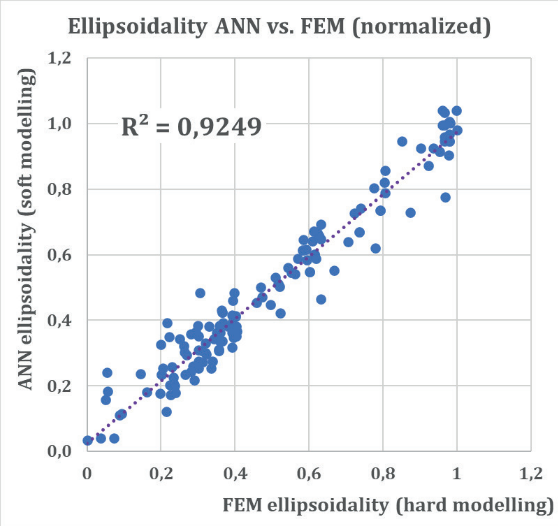


Fig. 4. Comparison of predicted ellipsoidality values for cases calculated by FEM (in order of decreasing values)

As shown in Figure 5a, a high agreement of the soft model with the results obtained from FEM modelling was obtained. The coefficient of determination R^2 shown in the graph was 0.92. A chart of the distribution of predicted values as a function of predicting errors is shown in Figure 5b. A group of predictions with an error of less than 10% makes up more than 60% of the set. Another 21% of observations were in the group of predictions with an error of less than 20%. Thirteen observations, which constitute 8.9% of the set, have a predicting error greater than 30%.



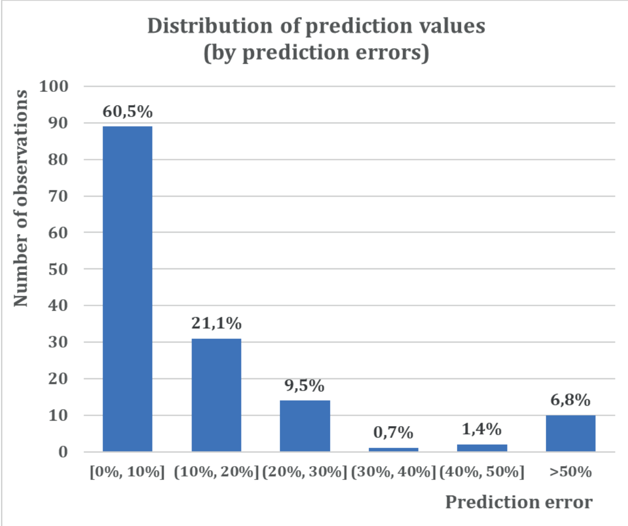


Fig. 5. Distribution of predicted values for ANN soft modelling as a function of values determined in FEM hard modelling (a) and distribution of predicted values as a function of prediction error (b)

3. Results of artificial neural networks modelling

The constructed neural network was used to generate the ellipsoidality quantity for any combination of input signals. For this purpose, a synthetic query set was developed. In the set, all input signals (see Table 1) took values at six normalised levels: 0.0; 0.2; 0.4; 0.6; 0.8; 1.0.

The developed prediction results for the combination of input signals allowed for the generation of graphs showing the impact of individual parameters in the set process conditions. Figure 6 shows the effect of the internal friction angle and the cohesion coefficient with constant properties: the mass Young's modulus, friction coefficient, profile material property coefficient ψ and profile wall thickness ($E = 0.0$; $\mu = 0.0$; $\psi = 0.0$; $g = 0.2$).

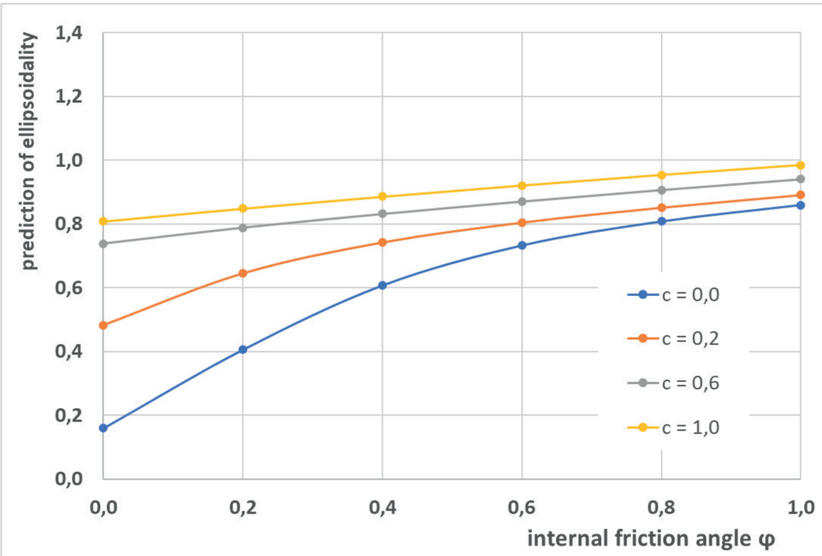


Fig. 6. Ellipsoidality (in normalised values) vs. angle of internal friction for the selected set of process parameters: $E = 0.0$; $\mu = 0.0$; $\psi = 0.0$; $g = 0.2$

As a result of changing one process parameter, e.g., Young's modulus of mass, we obtain analogous graphs (shown in Figure 7) with higher values of ellipsoidality. It can be observed the normalised ellipsoidality values exceed 1.0 which may indicate the potential of the technology to obtain greater deformations.

Changing the profile wall thickness from 0.2 (Fig. 7) to 0.8 mm (Fig. 8) not only shows that significantly higher ellipsoidality can be obtained but also a substantial transformation of profile behaviour can be observed.

The analysis of the wall thickness change showed that the increase of ellipsoidality with the increase of Young's modulus of mass is not a rule, which was observed in Figure 7 and Figure 8. The ANN prediction of ellipsoidality is shown in Figure 9. The summary shows that for tubes with a greater wall thickness ($g = 0.8$ and $g = 1.0$ for normalised values), flexible masses with low Young's modulus are better for achieving high ellipsoidality.

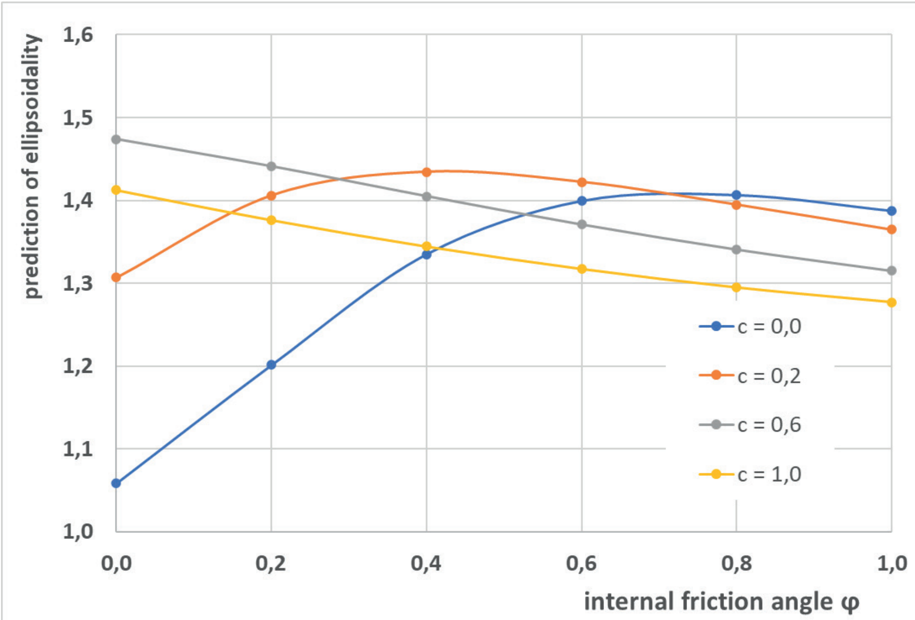


Fig. 8. Ellipsoidality (in normalised values) vs. angle of internal friction for the selected set of process parameters: $E = 1.0$; $\mu = 0.0$; $\psi = 0.0$; $g = 0.8$

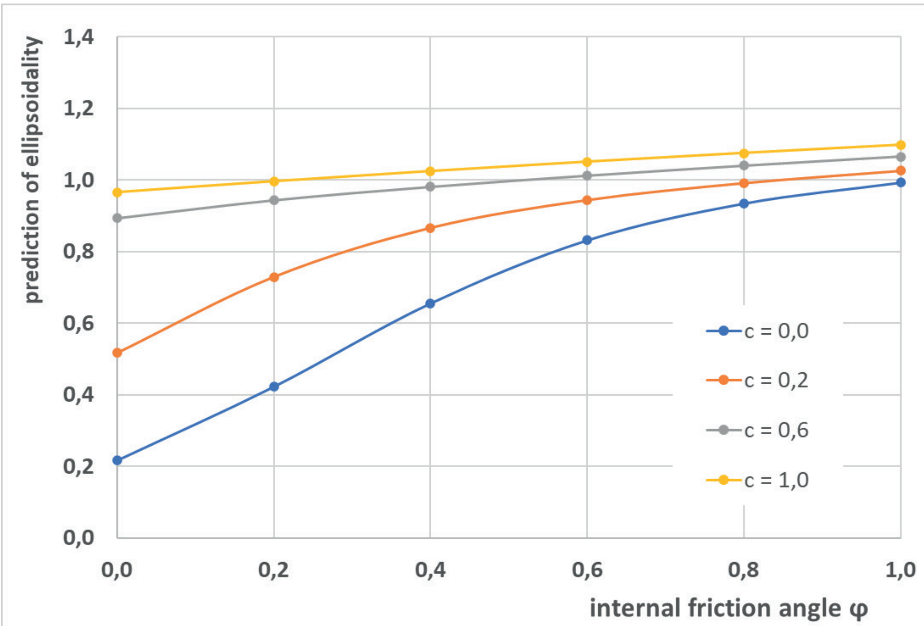
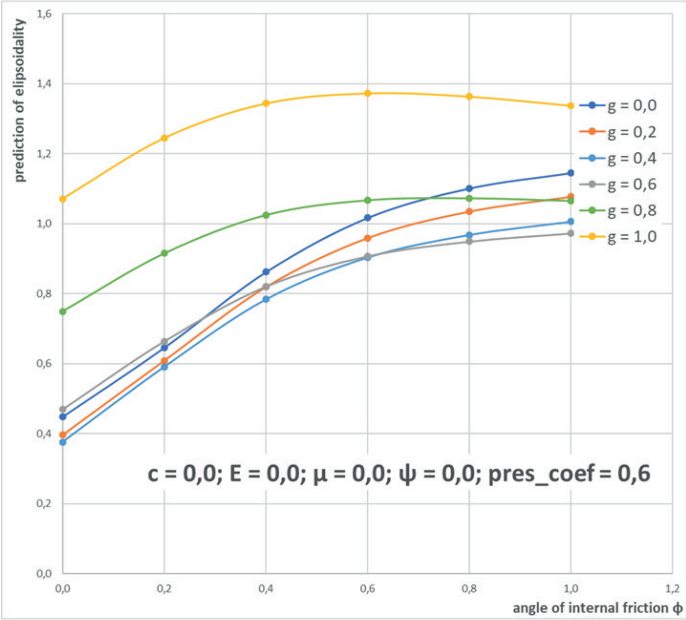


Fig. 7. Ellipsoidality (in normalised values) vs. angle of internal friction for the selected set of process parameters: $E = 1.0$; $\mu = 0.0$; $\psi = 0.0$; $g = 0.2$



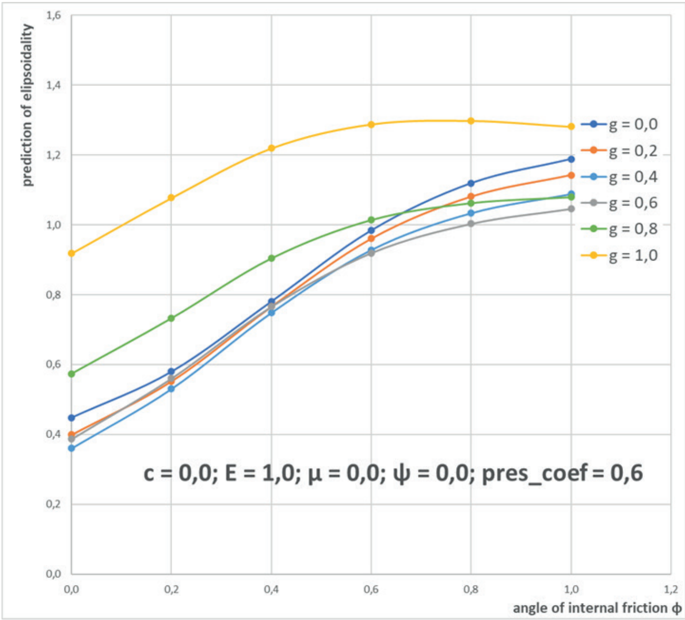


Fig. 9. Ellipsoidality (in normalised values) vs. angle of internal friction for the selected set of process parameters: a) $c = 0.0$; $E = 0.0$; $\mu = 0.0$; $\psi = 0.0$; b) $c = 0.0$; $E = 1.0$; $\mu = 0.0$; $\psi = 0.0$

In view of the above, it was considered appropriate to determine the significance of the impact of individual process parameters. The developed RTH method requires the selection of numerous mass properties to assess an ability to obtain maximum ellipsoidality for a profile with specific parameters (profile material, wall thickness, etc.). Therefore, some statistics were developed for cohesion and the angle of internal friction for all cases (all possible combinations) of other parameters to confirm or reject a hypothesis about the significance of the influence of these mass parameters.

The cohesion coefficient and the internal friction angle have been analysed to investigate their influence on ellipsoidality as the main mass parameters. Therefore, the ranges of both parameters are divided into six sections (according to normalised values) and the box charts for ellipsoidality have been arranged, see Figure 10. For both parameters, box charts show the ellipsoidality increase for each subsequent section with this trend being even more obvious for cohesion. Median values for individual sections of ellipsoidality vs. cohesion (Fig. 10a), vary from 0.39 to 0.77, while for internal friction angle from 0.41 to 0.72. According to the box charts, it can be hypothesized that both cohesion and internal friction angle affect ellipsoidality.

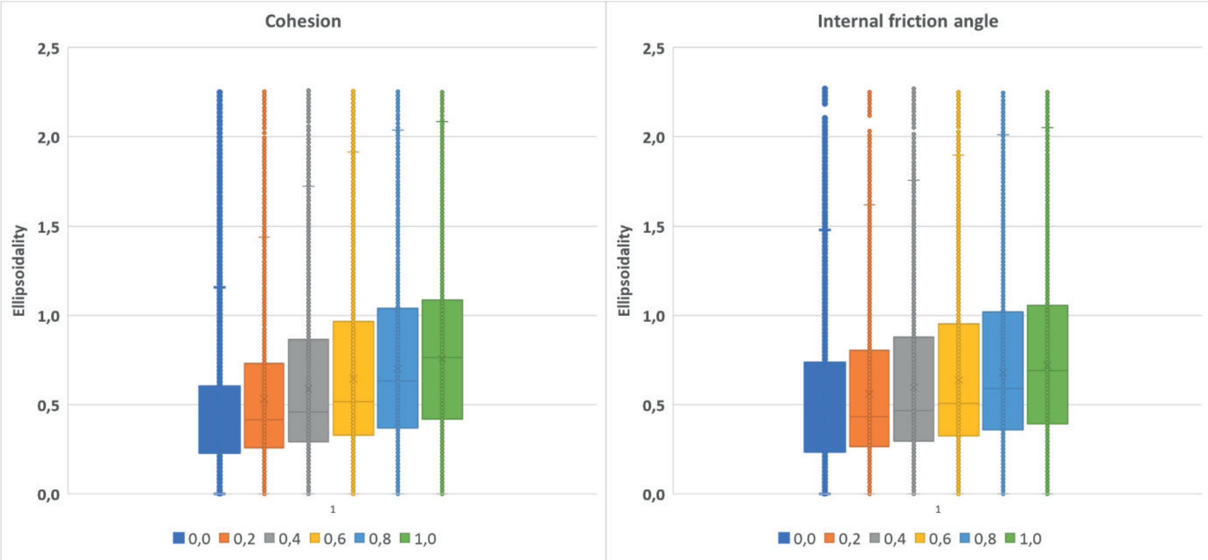


Fig. 10. Box charts for ellipsoidality data for: a) cohesion; b) internal friction angle

To confirm these statistically, and to establish that both parameters are correlated with ellipsoidality, two types of statistical tests were performed. The first test was the Kruskal–Wallis one-way analysis of variance by ranks test which is a non-parametric method used for testing whether samples originate from the same distribution (Kruskal & Wallis, 1952). The method is used to determine whether a statistically significant difference between the medians of three or more independent groups exists or not. In these considerations, the aim was to assess whether any samples (corresponding to each of six levels of the parameter) stochastically dominate one other, and thus whether it affects the ellipsoidality. The calculated value of the statistic for cohesion was 15,077, and for the angle of internal friction was 8063.9. Such large statistical values could be associated with various data taken for analysis (over 300,000). Regardless, for both parameters, the p-value was less than 2.2e-16, which indicates that there are statistically significant differences between the considered ranges.

In the next step of statistical analysis on ellipsoidality the Jonckheere–Terpstra test was carried out for an ordered alternative hypothesis within an independent samples design (Jonckheere, 1954; Terpstra, 1952). It is similar to the Kruskal–Wallis test in the null hypothesis claiming that several independent samples come from the same population (the medians are identical). The Jonckheere–Terpstra test has more statistical power than the Kruskal–Wallis test when there is an a priori ordering of the populations from which the samples are drawn, which fits perfectly into the analysis where ellipsoidality was divided into six ordered intervals for both cohesion and angle of friction. As noted above, some tendency of cohesion and angle of friction on ellipsoidality can be observed in the box charts (Fig. 10), but conducting the Jonckheere–Terpstra test and obtaining for both cases a p-value less than 2.3e-16 confirms that there is a statistically significant order between groups, i.e. depending on the increase in the value of cohesion and the angle of friction, ellipsoidality has an increasing trend.

4. Summary and discussion

The essence of shaping profiles by hydroforming is to obtain a product with a given shape, one which is significantly different from the initial one. An additional condition is that shaping the new cross-sectional geometry does not lead to the thinning of the profile wall. In the case of the newly developing RTH method, obtaining a state of large changes in shape with a low wall thinning would require a huge number of bench experiments. The approach shown in the paper allows for a significant acceleration of work and the indication of attractive, prospective research directions. The use of a soft mathematical model (ANN) based on the results of constitutive modelling (FEM) allowed for the analysis of the influence of selected process parameters on the product property, i.e., ellipsoidality.

The Kruskal–Wallis statistical tests carried out on the data from the soft model showed that there is a significance of the parameter under study (ellipsoidality) on both analysed parameters, i.e., mass cohesion and internal friction. The performed Jonckheere–Terpstra tests showed that the change in ellipsoidality was in a statistically significant way in terms of these two parameters. With the increase of the cohesion coefficient and the internal friction angle, the ellipsoidal index increases.

The values of ellipsoidality obtained because of ANN modelling (shown in) indicate the possibility of obtaining much greater ellipsoidality of the profile than obtained to date in bench tests.

5. Conclusions

The number of factors revealed in the Introduction indicates that the new technological process is very complicated and also difficult in terms of the number of factors that should be controlled during its implementation. As a result of the expert assessment, a limited number of parameters were distinguished, which satisfactorily allowed for:

– building a soft mathematical model approximating the behaviour of the shaped profile;
– preparation of a set of observations from numerical modelling allowing for initial testing of hypotheses about the significance of the impact of individual parameters;
– indication of prospective directions of bench research, in conditions of a clear reduction in the number of necessary experiments;
– development of assumptions for the preparation of a more reliable model allowing for the optimisation of the process conditions according to the selected criteria.

Moreover, the two-stage procedure proposed in section 2 allows for a significant reduction in the time needed to develop directions of action with significant research potential.

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