

Prediction of Load in Reverse Extrusion Process of Hollow Parts using Modern Artificial Intelligence Approaches

M. Shariat Panahi*, N. Moshtaghi Yazdani**

Department of Mechanical Engineering, University of Tehran

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ABSTRACT

Extrusion is one of the important processes to manufacture and produce military and industrial components. Designing its tools is usually associated with trial and error and needs great expertise and adequate experience. Reverse extrusion process is known as one of the common processes for production of hollow parts with closed ends. The significant load required in formation of a workpiece is one of the existing constraints for the reverse extrusion process. This issue becomes rather difficult especially for the parts having thin walls since its analysis using finite element softwares is exposed to some limitations. In this regard, application of artificial intelligence for prediction of load in the reverse extrusion process will not only save time and money, but also improve quality features of the product. Based on the existing data and methods suggested for variations of punching force through the reverse extrusion process, the system is trained and then performance of the system is evaluated using the test data in this paper. Efficiency of the proposed method is also assessed via comparison with the results of others.

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Corresponding Author:

N. Moshtaghi Yazdani,
Department of Mechatronics,
University of Tehran Kish International Campus,
Kish Island, Iran.
Email: navid.moshtaghi@ut.ac.ir

1. INTRODUCTION

Extrusion is a simple forming process in which a precast billet is first put in cylinder of the extrusion machine. Then, this billet flows outward from the die that is in direct contact with the cylinder by application of a great load which is introduced hydraulically or mechanically [1].

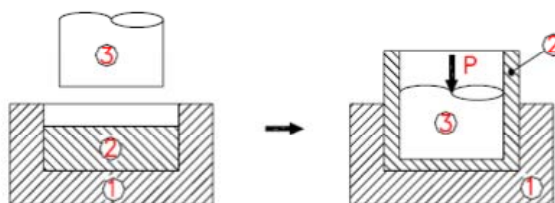


Figure 1. Reverse extrusion process: (1) die; (2) workpiece; and (3) punch

Extrusion is mainly divided into three groups in terms of deformation and type of the process: direct extrusion, indirect extrusion, 3333.

In direct (forward) extrusion, the punch and the die have horizontal positions, whereas the material under deformation and the punch move in the same direction. The load is applied to end of the billet with the metal flowing toward the force. There is some friction between the billet and the cylinder surrounding it. This technique has an advantageous simple design and in hot direct extrusion, the extruded workpiece can be easily controlled and cooled. Nevertheless, existence of friction in the contact area between the billet and the cylinder and heat generated thereof, formation of non-uniform microstructure and thus non-uniform properties along the extruded workpiece, greater deformation load in comparison with non-direct extrusion, as well as formation of internal defects particularly in existence of friction, introduction of surface and subsurface impurities to the workpiece, appearance of funnel-shaped cavity at the end of the billet and thus, excessive thickness of the remaining billet as scrap are some serious disadvantages of the direct extrusion.

Indirect (backward or reverse) extrusion is the same as the direct extrusion process except that the punch is fixed while the die moves [2]. Flow of the metal is opposite to the load application. Moreover, there is no friction between the billet and its surrounding cylinder. Taking into account hollow shape of the punch in the indirect extrusion process, there are practically some limitations in terms of the load as compared to the direct extrusion. This method benefits from several advantages; including 20-30% smaller load required in comparison with the direct extrusion owing to its no-friction condition, and temperature on outer layer of the billet is not increased because there is no friction between the billet and the cylinder. As a result, deformation will become uniform and formation of defects and cracks on corners and surface of the product will be diminished. The indirect extrusion process at high deformation rates is possible especially for aluminum materials which are pressed with difficulty.

Surface impurities of the billet do enter the final product so that the funnel-shaped cavity is not formed due to existence of friction. But instead, these impurities can also appear on surface of the workpiece. Life of the deformation tool especially inner layer of the cylinder is enhanced due to existence of the friction. Indirect extrusion has some disadvantages in spite of its numerous advantages, including limited deformation load, less facilities for cooling the extruded workpiece after leaving the die, lower quality of outer surface of the product.

Impact extrusion acts by performing impacts in which die and punch are positioned vertically and the punch impacts on the billet to give shape of the die and its surrounding cylinder. This forming process is sometimes known as a type of forging processes.

Economic significance of the impact extrusion is associated with effective application of raw material, reduced labor costs, elimination of intermediate operations, improved quality of the product, and great yield with relatively simple tools. Some advantages of this method are listed below: saving in consumption of the raw materials since all or a major part of the initial billet is transformed to the final product and the amount of wasted raw material is negligible, reduction or elimination of the final machining tools; examples prepared by this method provide acceptable dimensional tolerances and surface roughness (350-750 μ m), so they are completely usable and need no further machining, using less expensive materials is possible, many of the parts, if manufactured by conventional machining techniques, will need a series of preliminary operations, like rolling, drawing and etc. prior to production, while in impact extrusion and by using a cylindrical billet, the final product can be produced through one single process, reduced costs of warehousing; this method is performed automatically, so the operations of loading, unloading and materials handling are considerably decreased, simplicity of the process; this process is really simple such that many of the components are made just through one step and there is no need to intermediate steps, great production capacity; small parts can be made more than 50 workpiece per minute and this rate reaches up to 15 parts per minutes for the larger parts, bottom thickness of the product is independent of its wall thickness, capability to manufacture parts with zero separation angle, providing excellent mechanical properties and making a single part from several components.

On the other hand, the following items may be mentioned as the main disadvantages of the impact extrusion: this process is sometimes uneconomic; for example production of alloyed steels and high carbon steels is not economic because they both require a significant pressure and several intermediate pressing and annealing operations, impact extrusion is usually limited to products of cylindrical, square, hexagonal and elliptical sections or other symmetrical geometries with hollow or solid cross sections, application of the impact extrusion is not recommended for manufacturing off-center parts having different wall thickness since they impose asymmetric and anisotropic loads to the tool during the forming process, ratio of length to diameter is limited for both the product and the billet itself, impact extrusion process is rather capital consuming with its equipment being relatively expensive; therefore, mass production would be needed to make the process economically feasible.

2. SIGNIFICANCE OF LOAD IN REVERSE EXTRUSION PROCESS

Indirect (reverse) extrusion is one of the most important processes in the extrusion process. Exact amounts of pressing load and capacity are critical because designing the die and punch, determination of the forming steps, and materials selection all depend on it. There are numerous factors which affect the extrusion load, some of the most important of which are material and properties of the work piece, initial cross section of the work piece, ratio of friction between the surfaces, shape of the work piece and punch, and temperature of the process. A great number of experimental, analytical and numerical methods have been addressed in the literature to study prediction of load in extrusion processes [3]. Experimental methods usually demonstrate poor performance in representing exact details of the process and have limited applications. Meanwhile, finite element and finite difference methods need great computational time and powerful computers. Among the existing analytical methods, upper bound theory is the one which gives relatively accurate answers in a short time by its simple formulization, even though the workpiece incorporates many complexities. Macdormott et al. [4] have used 8 basic elements via the abovementioned method in order to predict the load required in forging process. Out of them, 4 ring elements belong to the inward flow, while the other 4 ring elements are related to the outward flow. Kiuchi et al. [5] have developed a method based on elemental upper bound technique for simulation of the metal forming processes (e.g. forging), in which straightforward elements have been used to obtain the forming force. Kim et al. [6] have estimated the material flow in the forging process using the elemental upper bound method. Thereby, they have become able to predict the preform geometry as well as the number of required forging steps in this process. Bae et al. [7] have adopted the elemental upper bound approach to analyze and get the load needed for the reverse extrusion process three dimensionally. The load increases throughout the workpiece due to growth of the friction surfaces at the final step and this regime is intensified at the final step.

3. KSTAR ALGORITHM

This is an example-based learner which classifies every new record by comparing it with the existing classified records in the database. It is assumed in this algorithm that the similar examples have the same classes. Two basic components of the example-based learners are distance function and classification function. The former determines the similarity between examples and the latter shows how similarity of the examples leads to a final class for the new example.

Kstar algorithm is a lazy learner of K-nearest neighborhood learning which uses a fatigue criterion to address distance or similarity of the examples to each other. The approach adopted by this algorithm to measure the distance between two examples is derived from information theory. In this regard, the distance between two examples includes the complexity of converting one example to another one. Measurement of the complexity is done in two steps: first, a constant set of conversions is defined which maps some examples to some other examples. A program for conversion of example "a" to example "b" involves a constant set of conversions which starts with "a" and ends to "b". These programs are typically made by adding a termination sign to each string. Complexity of a program is generally defined as length of the shortest string representing it. Therefore, the distance between two examples is length of the shortest string which converts two examples to one another. This approach concentrates on one conversion (the shortest one) among all the possible conversions [8].

4. SVM ALGORITHM

SVM is an algorithm for classification of linear and nonlinear data. It initially uses a nonlinear mapping for conversion of the initial data to higher dimensions and later looks for the best hyper-plane in the new dimensions. This hyper-plane includes a decision boundary which separates records of one class from other classes. The data marked as belonging to different classes are simply separated by a hyper-plane with a nonlinear mapping. SVM finds this hyper-plane using support vectors and margins which are defined by the support vectors. There are various decision boundaries for separation of the data associated with every class. However, current research work aims to find the decision boundary or the separating hyper-plane with maximum margin (i.e. maximum margin hyper-plane or MMH) which separates the data at greater accuracy and lower error. A data is deemed linear when it is separable by using a linear decision boundary. No direct line may separate data from different classes when the data is nonlinear. For those data which are separable linearly, the support vectors are a subset of learning records which are located on the margins. Nevertheless, the problem is a bit different for the nonlinear data.

Once the MMH and support vectors are obtained, a learnt SVM would be available. A learnt SVM is found as a function of support vectors, test records, constants and Lagrangean parameters versus support

vectors by equations related to the margins and hyper-plane followed by rewriting of them by Lagrangean formula and solving this problem by HHR conditions.

The approach utilized for a linear SVM can also be extended for creating a nonlinear SVM. Such an algorithm of SVM can get nonlinear decision boundary for the input space. Development of this approach has two main steps: in the first step, the input data is transferred to one higher dimension using a nonlinear mapping. There are a large number of nonlinear mappings at this step which can be utilized for this purpose. Once the data were mapped to a space of higher dimensions, the second step will search the new space for the linear separating hyper-plane. Finally, an optimization problem of second degree will be obtained which can be solved by linear SVM formula. The MMH found in the new space is indicative of a nonlinear hyper-plane in the initial space [9].

5. XCS ALGORITHM

An extensive range of learning algorithms are employed either supervised or not in the context of machine learning to stop the machine from searching a large volume of information and data. It further suggests a pattern which can be used for the predictable (classification and regression) or descriptive (clustering) actions. Techniques which work based on rules are known as the most famous machine learning methods, since they are more comprehensible in comparison with other techniques thanks to the approaches they commonly adopt.

They use a limited set of “action” and “condition” rules to show a small contribution of the whole solution space. The conditions address a part of the problem domain, whereas the actions indicate the decision based on the sub-problems specified by the condition. Basically, the classification systems include a set of rules in which every rule is an appropriate solution for the target problem. These classifications gradually become effective by application of a reinforcement plan which has genetic algorithms on its separators.

The first classification system was proposed by Holland in order to work for both the individual problems and continuous problems (LCS). This learning system classifies an example of the machine learning which combines temporal differences and learner’s supervisions with genetic algorithm and solves simple and difficult problems. According to the supervision suggested by Holland, the LCS uses a single property (called power) for each of the classifiers. Power of a separator denotes affectability of it and is exclusively determined by percentage the answer correlates with the expected results. These criteria are characterized by principles of supervisory training.

From the first introduction of the main learning classification systems (LCS), some other types of the LCS are proposed so far including XCS. Before 1995 when the extended classification system was not developed yet, ability of a classification system to find proper answers in the reinforcement system of these classifiers was of major concern. Thereby, basic and simple classification systems were changed to more accurate decision making factors. Now, it is firmly believed that the XCS is able to solve even more complicated problems with no need to further adjust the parameters. As a result, it is currently accounted for the most successful learning system.

6. IMPROVED XCS

In the suggested method, firstly the limited set of training data is commonly applied for amending characteristics of rules consists of prediction, prediction error and fitness. This is done by means of the following relation:

Updating prediction and prediction error

$$\text{If } \text{exp}_i < 1/\beta \text{ then } P_i = P_i + (R - P_i) / \text{exp}_i, \quad \epsilon_i = \epsilon_i + (|R - P_i| - \epsilon_i) / \text{exp}_i \quad (1)$$

$$\text{If } \text{exp}_i \geq 1/\beta \text{ then } P_i = P_i + \beta (R - P_i), \quad \epsilon_i = \epsilon_i + \beta (|R - P_i| - \epsilon_i) \quad (2)$$

Updating fitness:

$$\text{If } \epsilon_i < \epsilon_0 \text{ then } k_i = 1 \quad (3)$$

$$\text{If } \epsilon_i \geq \epsilon_0 \text{ then } k_i = \beta (\epsilon_i / \epsilon_0) - \gamma \quad (4)$$

$$F_i = f_i + \beta [(k_i / \sum k_j) - f_i] \quad (5)$$

In these relations, β is learning rank, γ is power of law accuracy, ε is prediction error, \exp is law experiment, P is law prediction, R is reward received from environment, k is law accuracy and f is fitness. i index also indicates number of law in set of rules.

In the next phase for developing variety in set of data, several couples were selected as parents from among the fields that display the part of existing data condition using the method of "Stochastic selection with remainder"², and new data condition section is created using intermediate crossover method which are applied on the fields of parents. In this method, the quantity of each of the conditional variables is obtained from the following relation:

$$a_i = \alpha(a_i^F) + (1-\alpha)(a_i^M) \quad (6)$$

in which a_i is the quantity of conditional variable of i in new data, a_i^F is the quantity of conditional variable i in the first parent (father), a_i^M is the quantity of conditional variable of i in the second parent (mother) and α is the coefficient of parents partnership which are determined in adaptive form. New data section performance is also produced using a non-linear mapping of conditional variables area to area of performance which are created by using the existing data.

Diversifying the existing data continues up to where learning stop condition (for example, when percent of system correct answers to the test data reach to a pre-determined threshold) is satisfied aided by completed data [11].

7. RESULTS AND DISCUSSION

Experiments [10] was selected in relation with the reverse extrusion process of aluminum parts in order to compare efficiency of the models developed by the abovementioned algorithms. The data extracted from these experiments contains some 240 data entries, out of which 200 entries are randomly selected for training with the remaining being chosen for testing.

Displacement of the punch, coefficient of friction, diameter of the punch, circumferential diameter of the die polygonal, and number of sides of the workpiece are taken as input variables of the problem, while the punching load is considered to be the output.

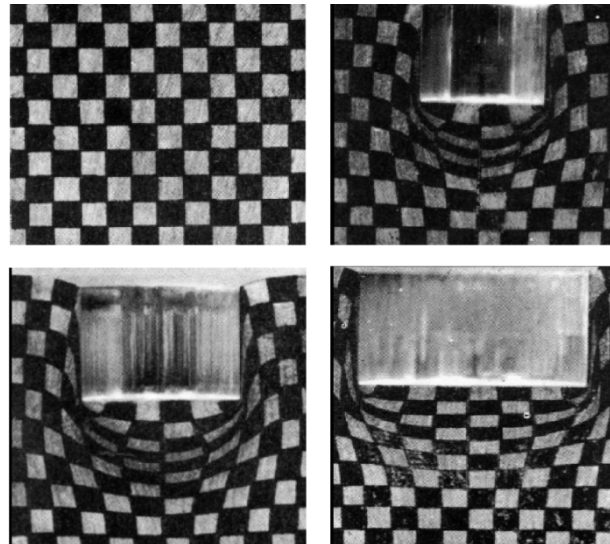


Figure 2. Practical testing of the reverse extrusion process

A comparison between the three trained algorithms gives the following results.

Table 1. Prediction of load in reverse extrusion process

Algorithm	Kstar	SVM	Improved xcs	XCS
Accuracy	83.9%	91.4%	92.8%	88.6%

8. CONCLUSION

Reverse extrusion is a common process for manufacturing hollow parts with closed ends and thus has numerous applications in different industries. The significant load required for forming the workpiece is one of the main drawbacks of the reverse extrusion process. A load prediction system is developed in this research based on the information gathered from reverse extrusion force analysis and artificial intelligence algorithms. These results may properly contribute to improve the reverse extrusion process considering accuracy of each of them in the test phase (as summarized in Table 1).

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