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Process Parameter Optimization for Minimizing Springback in Cold Drawing Process of Seamless Tubes Using Advanced Optimization Algorithms

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ABSTRACT

In tube drawing process, a tube is pulled out through a die and a plug to reduce its diameter and thickness as per the requirement. Dimensional accuracy of cold drawn tubes plays a vital role in the further quality of end products and controlling rejection in manufacturing processes of these end products. Springback phenomenon is the elastic strain recovery after removal of forming loads, causes geometrical inaccuracies in drawn tubes. Further, this leads to difficulty in achieving close dimensional tolerances. In the present work springback of EN 8 D tube material is studied for various cold drawing parameters. The process parameters in this work include die semi-angle, land width and drawing speed. The experimentation is done using Taguchi's L36 orthogonal array, and then optimization is done in data analysis software Minitab 17. The results of ANOVA shows that 15 degrees die semi-angle, 5 mm land width and 6 m/min drawing speed yields least springback. Furthermore, optimization algorithms named Particle Swarm Optimization (PSO), Simulated Annealing (SA) and Genetic Algorithm (GA) are applied which shows that 15 degrees die semi-angle, 10 mm land width and 8 m/min drawing speed results in minimal springback with almost 10.5 % improvement. Finally, the results of experimentation are validated with Finite Element Analysis technique using ANSYS.

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1. Introduction

This work is an extension of research conducted by Karanjule *et al.* [1]. Cold drawing is a manufacturing process carried out at room temperature which uses tensile forces to stretch the metal. In cold drawing operation, finished cold drawn tubes are produced by drawing hollow tubes through a die and plug to achieve close dimensional tolerances. Tube drawing process can be a single pass or multiple passes where a tube is pulled out from a steel conical die and a plug, to reduce both diameter and tube thickness. Cold drawn tubes are extensively used in automotive, petroleum, mining and bearing industries for manufacturing of various components, bearings, drill rods and line pipes. Dimensional accuracy has immense importance in the quality of end products and controlling rejection in manufacturing processes of these end products. However, springback causes geometrical inaccuracies in drawn tubes. Further, this leads to difficulty in achieving close dimensional tolerances. Springback phenomenon is related to the elastic strain recovery and physically governed by the stress state of the formed parts. To curb spring back, various factors such as tube drawing parameters and material properties need to be considered.

Many methods are suggested in case of the optimization purpose of process parameters like Genetic Algorithm (GA), Grey Relational Analysis (GRA), Regression Analysis (RA), etc. Most of the manufacturing processes use Taguchi method for the designing experiments and Analysis of Variance (ANOVA) to find the significant parameters of the process.

Liao *et al.* [2] investigated WEDM parameters in machining of SKD11 alloy steel using Taguchi method and ANOVA analysis. Spedding and Wang [3] tried to model the surface roughness, cutting speed and surface waviness in wire EDM process using a combination of artificial neural networks (ANNs) and response surface methodology. The pulse width, duration of the pulse, injection setpoint and wire tension were selected as input parameters. Puri and Bhattacharyya [4] conducted experiments which employed Taguchi method for thirteen control factors in the WEDM process, Tosun, and Pihtili [5] modeled output variables of WEDM parameters of machining with the help of regression analysis technique. Simulated annealing was then applied to find the machining parameters for multiobjective optimization of kerf and MRR. A combination of finite element model validated through trial experiments, and face-centered central composite design was used by Hosseinzadeh and Mouziraji [6] to design a matrix. Then, response surface methodology (RSM) was used to correlate empirical relationships between process factors and responses. The developed RSM models were then used to find the effects of tube drawing parameters and for the selection of optimum process parameters to achieve the desired quality regarding tube drawing performance in producing squared sections from round tubes. Tong and Su [7] stated multi optimization problems using Taguchi method for determination of quality loss, S/N ratio, and optimal factors. In this paper validation of optimum setting was conducted using confirmation experiments. Das *et al.* [8], Choudhury and Apparao [9] and Choudhury *et al.* [10] developed different models for optimization of process parameters for different responses such as surface roughness, tool wear, vibrations, etc. Antony [11] presented an optimization process of production with hot forming methods to maintain a metal

ring into a plastic body by Taguchi method. Singh and Kumar [12] optimized the characteristics of multi machining using utility concept and Taguchi parameter approach simultaneously. Lan and Wang [13] used L9 orthogonal array of Taguchi method for optimizing the multi-objective machining in CNC with material removal rate (MRR), tool wear and surface roughness as a response. Gopalsamy *et al.* [14] applied Taguchi method for studying the optimum parameters of machining of hard steel and used L18 orthogonal array for studying the characteristics of machining parameters viz. depth of cut, cutting speed, the width of cut and feed by considering tool life and surface finish as a response. Loharkar and Pradhan [15] described the state of research scenario in the field of cold drawing process analysis with a focus on various parameters and methods. Work carried out in this context described briefly along with the steps to carry out finite element analysis. It has also accounted for methods to design experiments and to optimize the process parameters.

Rajendrakumar, *et al.* [16], Ficici *et al.* [17], Kanlayasiri and Boonmung [18] studied different process parameters effects with Taguchi method. Sanchez *et al.* [19] presented a systematic approach to predict a wire EDM taper cutting angular errors using the design of experiments (DoE) techniques. Karunamoorthy and Ramakrishnan [20] developed multi-response optimization technique and artificial neural network (ANN) models for cutting parameter optimization for wire electro-discharge machining process using Taguchi's L-9 orthogonal array. Tarng, *et al.* [21] employed the fuzzy logic and Taguchi technique for submerged arc welding process optimization in which an ANOVA, signal-to-noise ratio, multi-response performance index were utilized to derive the characteristics of performance. Liao *et al.* [22] used the grey relational analysis along with Taguchi's quality concept to find the optimum machining parameters for the WEDM process using L18 mixed orthogonal array for experimental design. Fung and Kang [19] implemented Taguchi method and principal component analysis for multi-response optimization in an injection-molding process. Walia *et al.* [23] introduced Taguchi method with a combination of the concept of utility for optimizing centrifugal assisted abrasive flow machining (CFAAFM) process. Singh and Kumar [24] optimized multi-machining characteristics through utility concept and Taguchi's approach. In that paper, a case study was discussed performance behavior of turning operation of EN 24 steel with inserts of coated carbide. Pan *et al.* [25] used a combination of grey relational analysis and Taguchi method for prediction of optimized parameters of cutting of titanium alloy by the process of YAG laser welding.

After a comprehensive literature study, it is found that scarce work done is done in the area of the cold drawing process. Hence this research work is focused on optimizing cold drawing process parameters to minimize the springback using advanced optimization algorithms. The study consist of experimentation on draw bench to measure springback experimentally and then applying advanced optimization algorithms viz. Particle Swarm Optimization (PSO), Simulated Annealing (SA) and Genetic Algorithm (GA) to optimize process parameters namely die semi-angle, land width and drawing speed. Finally, the results of experiments are validated using Finite Element Analysis.

2. Experimental analysis

Cold drawing of seamless tubes on draw bench is carried out to check the minimum variation in the drawn tube. Less the variation from targeted value, less is the springback. The ultimate aim of this study is to decide best parameter setting for a particular tube and die material combination.

2.1. Materials

AISI D3 die steel is taken for die and plug materials having the capability of high wear, abrasion resistance and resistance to heavy pressure. This steel is widely used in industrial applications for different dies used in manufacturing processes like blanking, cold forming, stamping, punches, etc.

Seamless Tubes of C-45(EN-8D) material cold drawn from size of 33.40 mm outer diameter and 4.00 mm wall thickness is considered in this study. The chemical composition for tube material of C-45(EN-8 D) consists 0.45% carbon, taken for study because more the percentage of carbon, more will be springback.

2.2. Machine tool

The experimentation is carried out on draw bench, as shown in Fig. 1 having strength 50 Tonn, maximum drawing speed of 10 m/min and a maximum width of drawn tube obtained is 30 mm. A draw bench for cold drawing seamless tubes includes a die control device, a plug control device including a plug having large and small diameter bearing portions and a draw unit. The die control device and the plug control device are moveable concerning each other for changing the cross-sectional reducing area between the reducing die and the plug.



Fig. 1. Draw bench.

2.3. Taguchi based design of experiments

Taguchi method is utilized to design orthogonal array (OA) for the three parameters viz. die semi-angle (DA), land width (LW) and drawing speed (DS) through two levels of DA and LW and three levels of DS. After discussions with industry experts and literature survey (Karanjule *et al.*), it is found that these three geometrical parameters are crucial from springback point of view. The draw bench can change speed, so three levels are considered. The experiments are conducted as per DoE approach using OA to reduce the number of experiments to be performed. Table 1 indicates process parameters and their levels.

Table 1

Factors and their levels.

Sr.No.	Process parameter factor	Unit	levels of factors		
			Level-I	Level-II	Level-III
1	Die semi angle (DA)	Degree	10	-----	15
2	Land width (LW)	Millimeter	5	-----	10
3	Drawing speed (DS)	Meter/min	4	6	8

Seamless tubes are cold drawn through a die of 30.0 mm. The drawn tube outer diameter is measured using digital micrometer of 1-micron accuracy. The variation from 30.0 mm is referred to be springback.

Design of experiments using an orthogonal array is used for experimentation as shown in Table2. The results of the experimentation for EN 8 D(C-45) tube material and AISI D3 die and plug material are tabulated, the variation from targeted size is noted as a springback.

3. Results and discussions

3.1. Selection of optimum levels

The main effect of the factors on springback for each level is calculated, and the optimum level of each parameter is identified. Detailed statistical analysis using Minitab 17 software shows that die semi-angle of 15 degrees, the land width of 5 mm and drawing speed of 6 m/min gives the least springback.

3.2. Confirmation of experiments

After identifying the optimum levels using the statistical technique, the confirmation experiments were conducted and the springback obtained was compared with that one obtained from initial parameter setting. The regression model is found adequate having R^2 value 98.44%, R^2 (adj) value 97.73% and R^2 (pred) value 96.50%.

Table 2

Experimental layout and results.

Sr.No.	Die semi angle (degree)	Land width (mm)	Drawing speed (m/min)	Actual measurement of OD (mm)	Springback (mm)
1	10	5	4	30.065	0.065
2	10	5	6	30.064	0.064
3	10	5	8	30.098	0.098
4	10	5	4	30.062	0.062
5	10	5	6	30.060	0.06
6	10	5	8	30.095	0.095
7	10	5	4	30.061	0.061
8	10	5	6	30.062	0.062
9	10	5	8	30.096	0.096
10	10	10	4	30.080	0.08
11	10	10	6	30.082	0.082
12	10	10	8	30.050	0.050
13	10	10	4	30.082	0.082
14	10	10	6	30.079	0.079
15	10	10	8	30.054	0.054
16	10	10	4	30.079	0.079
17	10	10	6	30.080	0.08
18	10	10	8	30.058	0.058
19	15	5	4	30.063	0.063
20	15	5	6	30.0248	0.0248
21	15	5	8	30.266	0.266
22	15	5	4	30.100	0.100
23	15	5	6	30.055	0.055
24	15	5	8	30.255	0.255
25	15	5	4	30.121	0.121
26	15	5	6	30.0258	0.0258
27	15	5	8	30.255	0.255
28	15	10	4	30.308	0.308
29	15	10	6	30.104	0.104
30	15	10	8	30.048	0.048
31	15	10	4	30.290	0.29
32	15	10	6	30.125	0.125
33	15	10	8	30.052	0.052
34	15	10	4	30.285	0.285
35	15	10	6	30.123	0.123
36	15	10	8	30.059	0.059

Table 3

Confirmatory test results.

Optimum factors	Regression model springback	Experimental value springback	% variation
15 degree die semi angle 5 mm land width 6 m/min drawing speed	0.021	0.0253	16.99

Consequently, these confirmatory tests give satisfactory results with 16.99 % variation which is acceptable as shown in Table 3 and revealed that the optimization process is significant.

3.3. Development of regression model

From measured springback, an empirical equation is developed with linear regression technique. The regression equation is calculated by mean values of springback under different conditions of input process parameters. Equation (1) indicates regression of springback(SB) in terms of die semi-angle, land width and drawing speed.

$$\text{Springback (SB)} = 0.871 - 0.0995 \times \text{DA} - 0.1543 \times \text{LW} - 0.1801 \times \text{DS} - 0.00148 \times \text{DS} \times \text{DS} + 0.01740 \times \text{DA} \times \text{LW} + 0.02235 \times \text{DA} \times \text{DS} + 0.02822 \times \text{LW} \times \text{DS} - 0.003167 \times \text{DA} \times \text{LW} \times \text{DS} \quad (1)$$

4. Optimization

An optimization algorithm is a procedure which is executed iteratively by comparing various solutions to the optimum, or a satisfactory solution is found. Optimization algorithms begin with one or more design solutions supplied by the user and then iteratively check new solutions to achieve a truly optimum solution.

The objective function is formulated (equation 1) for applying different algorithms viz. Particle Swarm Optimization (PSO), Simulated Annealing (SA), Genetic Algorithm (GA).

4.1. Particle swarm optimization (PSO)

PSO is a multi-agent parallel search technique. Particles are conceptual entities, which fly through the multi-dimensional search space. At any particular instant, each particle has a position and a velocity. The position vector of a particle concerning the origin of the search space represents a trial solution of the search problem. The flowchart for this algorithm is as shown in Fig. 2.

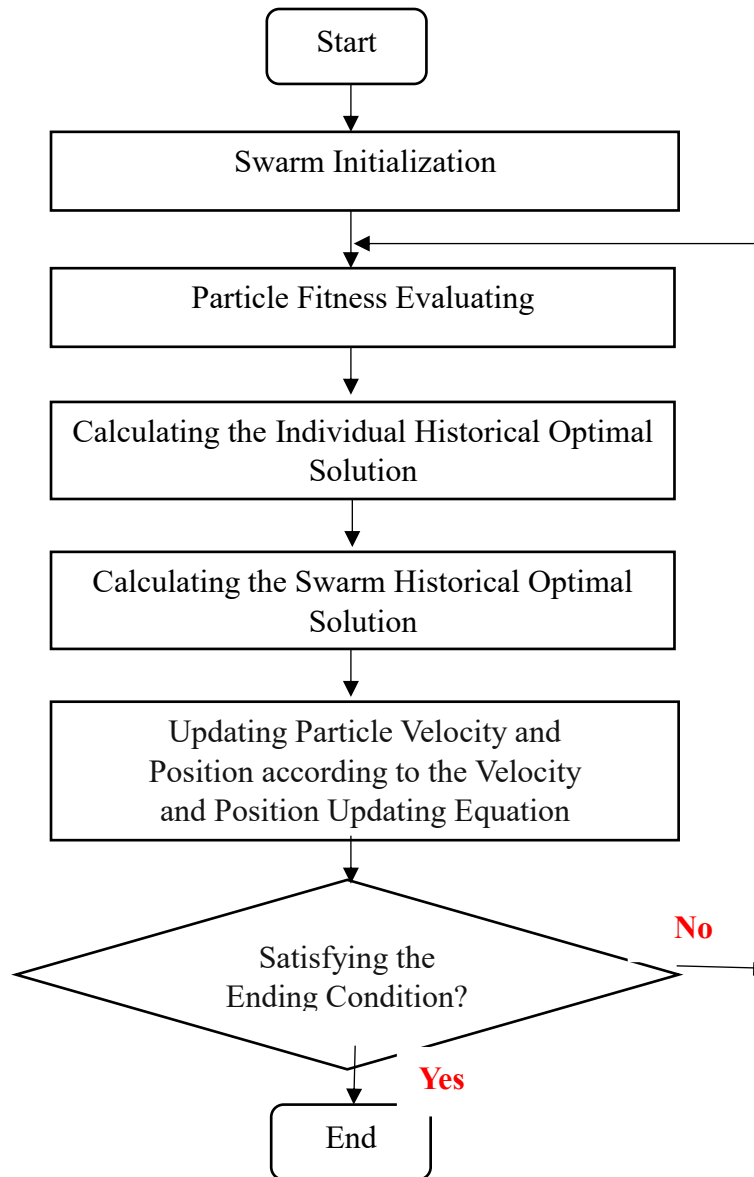


Fig. 2. Flow chart for Particle Swarm Optimization (PSO).

Optimization using Matlab coding as shown in appendix A, the minimum value of the springback obtained with Particle Swarm optimization is 0.0492 for the parameter setting of 15 degrees die semi-angle, 10 mm land width and 8 m/min drawing speed.

4.2. Simulated annealing

The Metropolis algorithm can be used to generate a sequence of solutions of a combinatorial optimization problem. A Simulated Annealing optimization starts with an initial solution to the problem, which is also the Best solution so far, and the temperature set at the initial, high-temperature $Temp(i)$. This solution becomes the Current solution and the Parent or active

solution. The number of Monte Carlo (ITRY) attempts set to zero. The flow chart for this algorithm is as shown in Fig.3.

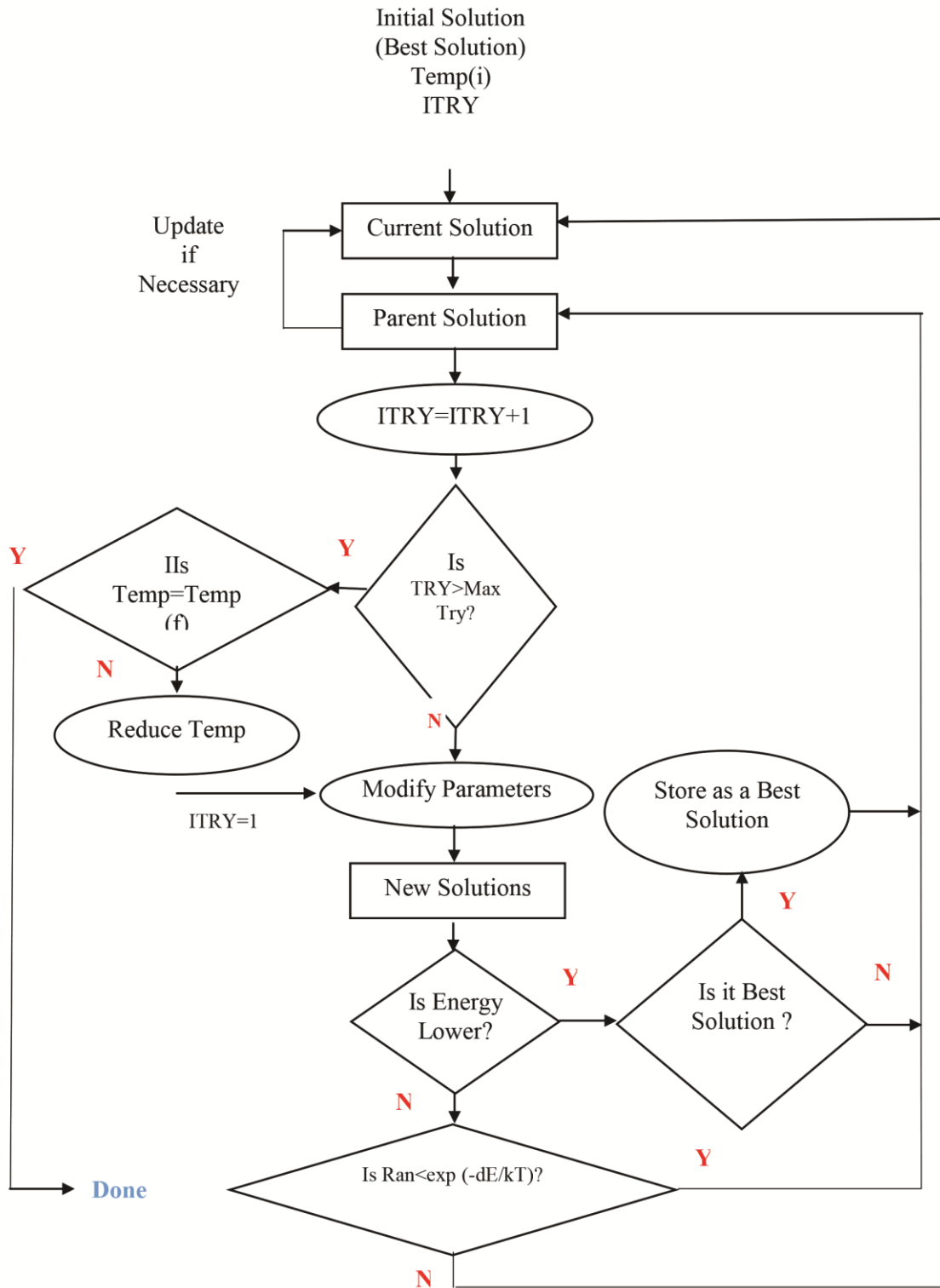


Fig. 3. Flow chart for Simulated Annealing (SA).

Optimization using Matlab coding as shown in Appendix B, the minimum value of springback obtained with Simulated annealing is 0.04918683709759275. With optimization terminated the best function values for the three parameters are as follows and are shown in Fig. 4.

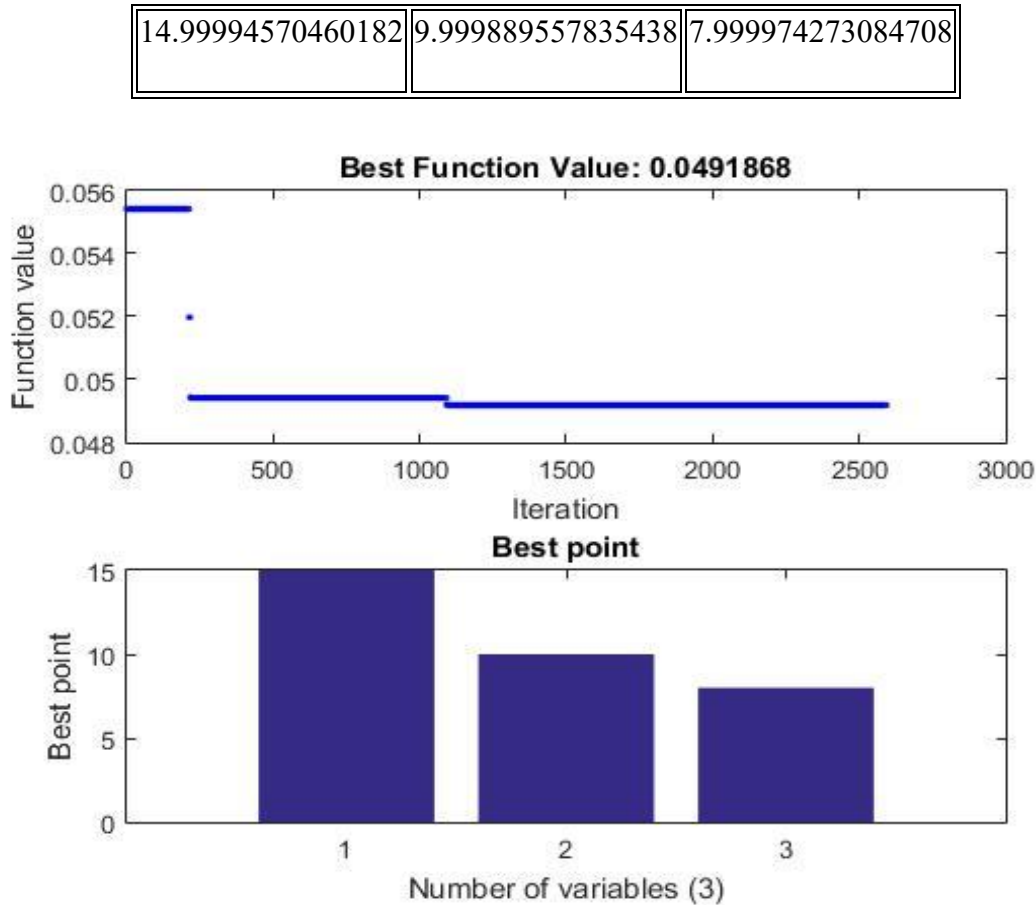


Fig. 4. Output of Simulated annealing.

4.3. Genetic algorithm

Genetic Algorithms (GA) are direct, parallel, stochastic method for global search and optimization, which imitates the evolution of the living beings, described by Charles Darwin. GA is part of the group of Evolutionary Algorithms (EA).

The GA algorithm

1. Generate initial population – in most of the algorithms, the first generation is randomly generated, by selecting the genes of the chromosomes among the allowed alphabet for the gene. Because of the easier computational procedure, it is accepted that all populations have the same number (N) of individuals.

2. Calculation of the values of the function that we want to minimize or maximize.

3. Check for termination of the algorithm – as, in the most optimization algorithms, it is possible to stop the genetic optimization by:

- Value of the function – the value of the function of the best individual is within a defined range around a set value. It is not recommended to use this criterion alone, because of the stochastic element in the search the procedure; the optimization might not finish within sensible time;
- A maximal number of iterations – this is the most widely used stopping criteria. It guarantees that the algorithms will give some results within some time, whenever it has reached the extreme or not;
- Stall generation – if within an initially set number of iterations (generations) there is no improvement in the value of the fitness function of the best individual, the algorithms stops.

4. Selection – Within the current population, individuals are chosen; who will continue and using crossover and mutation will produce offspring population. At this stage elitism could be used – the best n individuals are directly transferred to the next generation. The elitism guarantees that the value of the optimization function cannot get worst (once the extremum is reached it would be kept).

5. Crossover – the individuals were chosen by selection, recombine with each other and new individuals will be created. The aim is to get offspring individuals, which inherit the best possible combination of the characteristics (genes) of their parents.

6. Mutation – using a random change of some of the genes, it is guaranteed that even if none of the individuals contain the necessary gene value for the extremum, it is still possible to reach the extremum.

7. The new generation – the elite individuals were chosen from the selection are combined with those who passed the crossover and mutation and form the next generation.

The flow chart for Genetic Algorithm is as shown in Fig. 5.

Optimization using Matlab gives following values and are shown in Fig. 6.

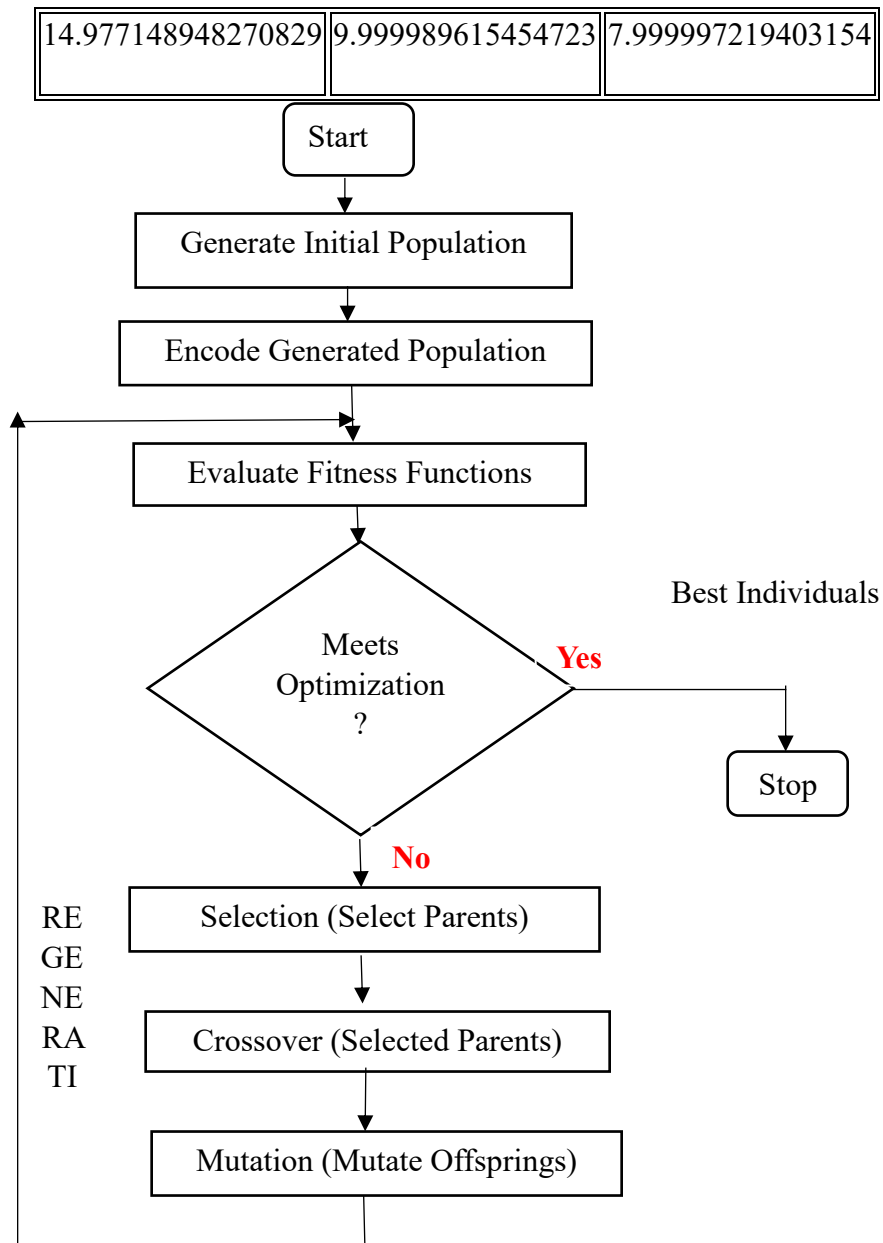


Fig. 5. Flow chart for Genetic Algorithm (GA).

Optimization using Matlab gives following values and are shown in Fig.6.

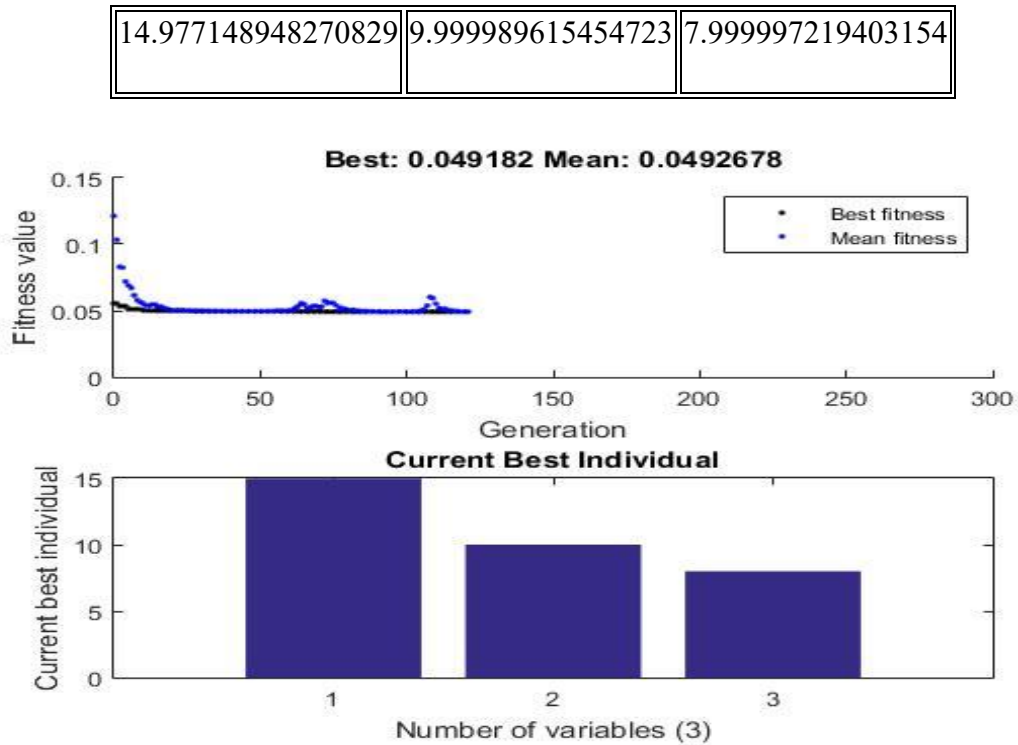


Fig. 6. Output of Genetic algorithm.

The comparative study of all these algorithms is tabulated as shown in Table 4.

Table 4
Comparison of springback for initial and optimal parameter setting.

Response	Initial Parameter setting	Optimal parameter setting using PSO	Optimal parameter setting using SA	Optimal parameter setting using GA
Parameter values	Die semi angle 15 Land width 5 Drawing speed 6	Die semi angle 15 Land width 10 Drawing speed 8	Die semi angle 15 Land width 10 Drawing speed 8	Die semi angle 15 Land width 10 Drawing speed 8
Springback	0.055	0.0492	0.0491868	0.049182
Improvement		5.8E-3	5.8132E-3	5.818E-3
% improvement		10.54 %	10.57 %	10.58 %

5. Finite element analysis

Finite element method is the numerical analysis technique to solve engineering problems based on stress analysis. The finite element procedure involves solving many simultaneous algebraic equations by using a computer. ANSYS is computer software used for finite element analysis.

PRO-E is one of the user-friendly software used for modeling of dies and plugs for drawing. 3D model consists of parts, assemblies, and drawings. In the simulation procedure, the die is considered to be rigid, the tube is rigid-plastic, and the interface between the tube and die has a constant friction coefficient. Finite element analysis recreates an actual engineering system accurately describing the mathematical model of a physical prototype. The model should indicate all the nodes, elements, material properties, real constants, boundary conditions, and other features representing the actual engineering system. In ANSYS model generation usually takes more time, hence the model is imported from PRO-E software.

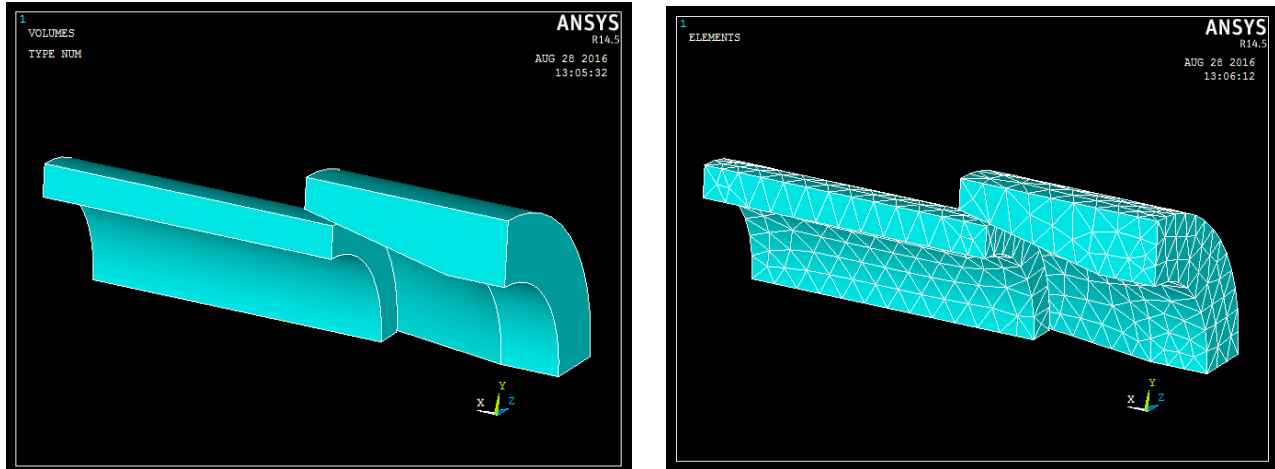


Fig. 4. Imported quarter section 3D model.

Once Finite element models were built, then as a material behavior, geometry and loading conditions are considered as axially symmetric, an axisymmetric model was used. Meshed the volume using smart size option in the mesh tool with proper size as shown in figure 4. Solid 45 is eight noded-hexahedral brick. The results are better sizes than solid 92 tetrahedral elements. The number of elements is 63172 and number of nodes are 69645. The cold drawing process is simulated using ANSYS. The tube material is C-45 with a modulus of elasticity $210,000 \text{ N/mm}^2$ and Poisson's ratio 0.29. The analysis is non-linear contact analysis. There is contact between die inner and tube outer surfaces as well as inner tube surface and plug outer surface. In the analysis, die is assumed to have a very high modulus of elasticity of $2.1 \times 10^9 \text{ N/mm}^2$. The pre-solver reads the model created in pre-processor and formulates the mathematical representation of the model. However, the post-solver calculates strains, stresses, heat fluxes, velocities, etc. for each node within the component or continuum. All these results are sent to a result file, which may be read by the post-processor.

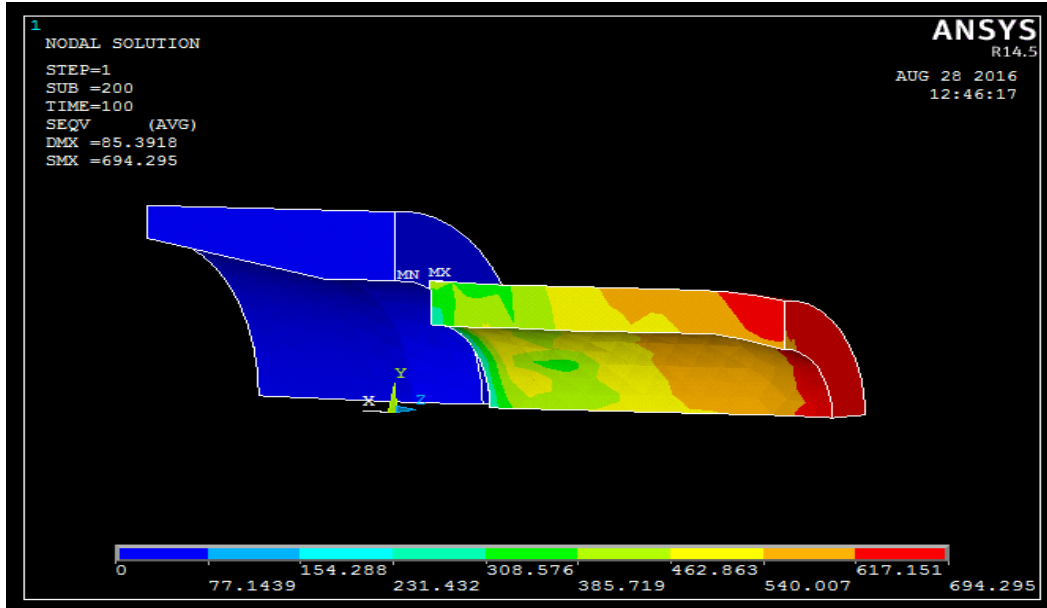


Fig. 5. Equivalent Von-Mises stress.

In this result, the equivalent Von-Mises stress is calculated. From Fig. 5, it observed that the minimum value of stress is observed at the die, whereas the maximum value of stress is observed at the end of the tube with the numerical value of 694.295 N/mm².

The equivalent plastic strain is the measure of the permanent strain found in an engineering body. Most of the engineering materials have a linear stress-strain relationship up to a stress level called as a proportional limit, beyond which the stress-strain relationship will no more linear, becomes nonlinear. In the simulation, we can observe the maximum value of strain is 0.20945 whereas minimum strain observed is 0.022919. The springback measured using ANSYS is tabulated as shown in Table 5.

Table 5
Springback results using FEA.

Tube no.	Average at location 1	Average at location 2	Average readings	Springback
1	30.0250	30.056	30.0405	0.0405
2	30.048	30.059	30.0535	0.0535
3	30.060	30.064	30.062	0.062

This research is a detailed simulation of cold drawing process for seamless tubes along with experimentation to study the springback effect. The actual drawing angles and die land width are used while modeling the process. To reduce the computer time and utilities the die, plug and the tube was modeled quarterly. The results of experimentation and finite element analysis are showing good agreement.

6. Conclusions

The present work has disclosed an optimized parameter setting to minimize springback for cold drawing of seamless tubes. Based on the experimentation, modeling and optimization following conclusions can be drawn.

- From the results of ANOVA, it is found that the major controllable parameter affecting the springback is die semi-angle with a contribution of 42.18%.
- The optimal combination predicted for cold drawing of seamless tubes of EN 8 D(C-45) material is 15 degrees die semi-angle, 5 mm land width and 6 m/min drawing speed.
- The optimization algorithms named PSO, SA and GA show that 15 degrees die semi-angle, 10 mm land width and 8 m/min drawing speed gives least springback.
- The optimization algorithms have effectively proved for the optimization of springback and have shown 10.54 % improvement by PSO, 10.57 % improvement by SA and 10.58 % improvement by GA.
- The springback measured with simulation is in good agreement with the experimental results.

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Appendix

A) The PSO algorithm

Input: Randomly initialized position and velocity of the particles: $X(0)$ and $V(0)$

Output: Position of the approximate global optima X^*

Begin

While terminating condition is not reached do

Begin

for $i = 1$ to number of particles

Evaluate the fitness:= $f(X_i)$;

Update p_i and g_i

Adapt velocity of the particle using equations (1);

Update the position of the particle;

increase i ;

end while

end

—
The objective function can be written as

Minimize SB = $0.871 - 0.0995 DA - 0.1543LW - 0.1801DS - 0.00148DS*DS + 0.01740DA*LW + 0.02235DA*DS + 0.02822LW*DS - 0.003167DA*LW*DS$

The lower and upper bounds are

$10 \leq \text{Die semi angle} \leq 15$

$5 \leq \text{Land width} \leq 10$

$4 \leq \text{Drawing speed} \leq 8$

These parametric values are given as input to PSO algorithm code written in Matlab and the optimum condition of input parameters are obtained as the output of the algorithm is analyzed.

function $y = \text{springback}(x)$

$y = (0.871 - 0.0995*x(1) - 0.1543*x(2) - 0.1801*x(3)$

$+ 0.00148*x(3)*x(3) + 0.01740*x(1)*x(2) + 0.02235*x(1)*x(3) + 0.02822*x(2)*x(3)$

$- 0.003167*x(1)*x(2)*x(3));$

$lb = [10; 5; 4];$

$ub = [15; 10; 8];$

$fun = @springback;$

$nvars = 3;$

$[x, fval, exitflag] = \text{particleswarm}(fun, nvars, lb, ub)$

```

options = optimoptions('particleswarm','SwarmSize',100);
[x,fval,exitflag] = particleswarm(fun,nvars,lb,ub,options)
options = optimoptions(@particleswarm,'OutputFcns',@pswplotranges);
[x,fval,exitflag] = particleswarm(fun,nvars,lb,ub,options)
x = 15 10 8
fval = 0.0492
exitflag = 1

```

B) The SA algorithm

```

begin
INITIALIZE (I start, Co, Lo);
k:=0;
i=I start
repeat
for / := 1 to Lk do
begin
GENERATE (j from si)
If  $f(j) \leq f(i)$  then i:=j
else
if  $\exp[(f(i)-f(j))/ck] > \text{random}[0, 1)$  then i := j
end;
k:=k + 1;
CALCULATE LENGTH (Lk);
CALCULATE CONTROL (Q);
until stopcriterion
end;
Here lb=[10;5;4];
ub=[15;10;8];
fun = @springback;
X0 = [10 5 4];
[x,fval,exitFlag,output] = simulannealbnd(ObjectiveFunction,X0,lb,ub);

```

C) Genetic algorithm

```

i = 0
Initialize population P0
Evaluate initial population
while ( ! termination condition)
{
i = i+1
Perform competitive selection
Create population Pi from Pi-1 by recombination and mutation
Evaluate population Pi
}

```
