Optimising fracture in automotive tail cap by firefly algorithm

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Abstract: Deep drawing is a manufacturing process in which sheet metal is progressively formed into a three-dimensional shape through the mechanical action of a punch forming the metal inside die. The flow of metal is complex mechanism. Pots, pans for cooking, containers, sinks, automobile body parts such as panels and gas tanks are among a few of the items manufactured by deep drawing. Uniform strain distribution in forming results in quality components. The predominant failure modes in sheet metal parts are springback, wrinkling and fracture. Fracture or necking occurs in a drawn part, which is under excessive tensile loading. The prediction and prevention of fracture depends on the design of tooling and selection of process parameters. Firefly algorithm is one of the nature inspired optimisation algorithms and is inspired by firefly's behaviour in nature. The proposed research work presents novel approach to optimise fracture in automotive component-tail cap. The optimisation problem has been defined to optimise fracture within the constraints of radius on die, radius on punch and blank holding force. Fire fly algorithm has been applied to find optimum process parameters. Numerical experimentation has been conducted to validate the results.

Keywords: firefly algorithm; deep drawing process; optimisation; fracture.

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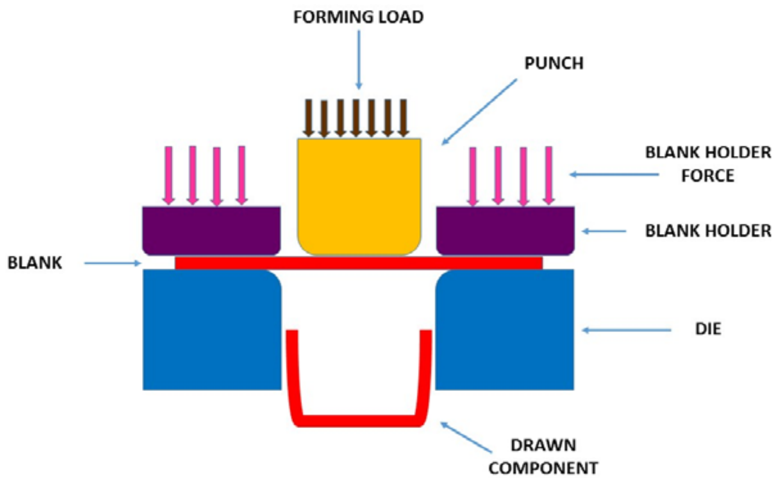
1 Introduction

1.1 Deep drawing: versatile manufacturing technique

The production of high quality formed products in a short time and at a low cost is an ultimate goal in manufacturing. Deep drawing is one of the extensively used sheet metal forming process, where depth of the part, being made is more than its diameter. It is extensively used to for making lightweight, high strength, low density, and corrosion resistible cylindrical shaped parts such as cups, shells, etc. from sheet metal (Ramesh and Reddy, 2013).

In this process sheet metal blank is radially drawn into a die cavity of required shape by the mechanical action of a punch. Smooth material flow is facilitated by radius on punch and radius on die. Friction condition also play crucial role. Blank holder assures controlled flow of blank inside die. Excessive blank holder force initiated fracture where as insufficient can generate wrinkles. As the blank is drawn into the die cavity, tensile forced acts in radial direction and compressive in circumferential direction. These two must be balanced with forming load otherwise wrinkle or fracture initiates. The four major defects, which can occur during deep drawing, are fracture, wrinkling, earring and springback (Patekar et al., 2016). If the process parameters are not properly selected, the component is likely to develop these defects. So, it is important to optimise the process parameters for avoiding defects and to minimise production costs. Parameters as blank-holder force, radius on punch, radius on die, material properties, and friction affect the flow of metal in die. This flow controls strain distribution in drawn component, which in turn determine the product quality. Figure 1 presents the schematic representation of the process.

Figure 1 Deep drawing process (see online version for colours)



2 Fracture in deep drawing

The fracture characteristic is not given by total elongation but is indicated by the cross-sectional area of the fracture surface after the test-piece has necked and failed. This is difficult to measure in thin sheet and consequently problems due to fracture may not be properly recognised. Traditionally, the formability of a fracture-free sheet metal product is predicted using the forming limit diagram (FLD). The forming limit of a sheet metal is defined to be a state at which the localised necking initiates (i.e., when the existing state of strain becomes unstable) as the sheet is formed into the product. This limit is conventionally represented as a curve in the 2D strain space of major and minor strains. This curve is called the FLD (Marciniak et al., 1992).

In so many cases after the sheet metal was successful drawn, the fracture at the shell of the specimens always occurred and thus making the product defective. It is one of the most common undesired outcomes. Fracture may be caused by excessive punch force, excessive blank holder force, excessive friction between blank and tooling, insufficient clearance between punch and die and insufficient punch or die corner radius (Wifi et al., 2007; Joshi et al., 2013; Kakandikar and Nandedkar, 2012; Singh and Agnihotri, 2015). Shell fracture is one of the outcomes commonly observed in deep drawing process (Kakandikar, 2014).

3 Optimisation

Optimisation is act of finding the best results under the given circumstances. Simply optimisation means to maximise the desired benefits or to minimise the required efforts in any engineering problem. In past several years, various metaheuristics techniques have been developed. They include number of nature/bio-inspired optimisation techniques such as evolutionary algorithms (EAs) and swarm intelligence (SI). Some of the SI techniques include particle swarm optimisation (PSO) (Ravindra Reddy et al., 2012), firefly algorithm (FA) (Kulkarni et al., 2015), Cuckoo search (CS) algorithm (Farahani et al., 2011), Grey Wolf optimiser (GWO) (Yang, X.S. and Ded, 2009), ant colony optimisation (ACO) (Mirjalili et al., 2014), artificial bee colony (ABC) algorithm (Dorigo and Gambardella, 1997), etc. The EAs consist of genetic algorithm (GA) (Karaboga and Akay, 2011), and differential evolution (DE) (Bhoskar et al., 2015), etc. Socio inspired algorithms such as cohort intelligence algorithm are also becoming popular (Qin et al., 2009; Omkar et al., 2016).

Researchers have highly attracted to all these metaheuristics methods due to added advantages. The simplicity in programming is major one; algorithm specific parameters are very low which makes it easy for implementation and suitability to majority of problems. Secondly they work with population; thoroughly exploring the search space with ensures that no potential solution has been neglected. The algorithm runs over generations/iterations until optimised solution is arrived at. Any kind of mathematical representation of objective function and constraints such as continuous, discrete, convex and concave does not affect the accuracy of solution. Many algorithms offer real as well as binary coding facilities. FA being very recent technique offers all these advantages to solve the problems, so it has been selected for the optimisation.

4 Firefly algorithm

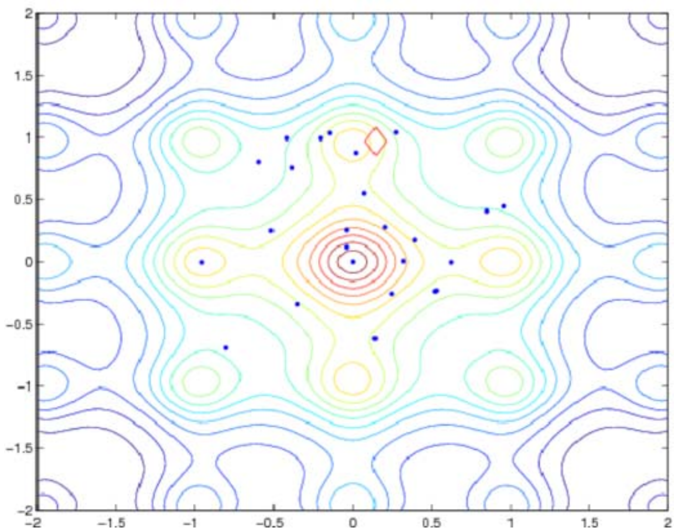
FA is one of the metaheuristics optimisation algorithms, which is inspired by mimicking the firefly's flashing behaviour and pattern in nature. Each firefly movement is based on absorption of the other one. The FA was developed by Yang (2009) and it is based on idealised behaviour of agents.

The algorithm is based on foundation of following three rules, which makes it simple and applicable to numerous fields:

- All fireflies are unisex, so that one firefly is attracted to other fireflies regardless of their sex (Kwiecień and Filipowicz, 2012).
- Attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less bright one will move towards the brighter one.
- The attractiveness is proportional to the brightness and they both decrease as their distance increases. If no one is brighter than a particular firefly, it will move randomly. The brightness of a firefly is affected and determined by the landscape of the objective function to be optimised.

The flashing light of fireflies is an amazing sight in the summer sky in the tropical and temperate regions. There are about 2,000 firefly species, and most fireflies create short and rhythmic flashes (Arora and Singh, 2013). The pattern of flashes is often unique for a particular species. The flashing light is produced by a process of bioluminescence, and the true functions of such signalling systems are still debating. However, two fundamental functions of such flashes are to attract mating partners (communication), and to attract potential prey (Yang, 2013). In addition, flashing may also serve as a protective warning mechanism. The rhythmic flash, the rate of flashing and the amount of time form part of the signal system that brings both sexes together. Females respond to a male's unique pattern of flashing in the same species, while in some species such as photuris, female fireflies can mimic the mating flashing pattern of other species so as to lure and eat the male fireflies who may mistake the flashes as a potential suitable mate (Hashmi et al., 2013). It is known that the light intensity at a particular distance r from the light source obeys the inverse square law. That is to say, the light intensity I decrease as the distance r increases in terms of I/1/r2 (Fister et al., 2013). Furthermore, the air absorbs light, which becomes weaker and weaker as the distance increases. These two combined factors make most fireflies visible only to a limited distance, usually several hundred metres at night, which is usually good enough for fireflies to communicate (Zhang et al., 2016).

Figure 2 Behaviour of fireflies (see online version for colours)



FA has got sufficient attraction by researchers due to its simplicity in implementation. Two major advantages over other algorithms are automatically subdivision and the ability of dealing with multimodality (Umbarkar et al., 2017). The firefly's forms subgroups of nearby agents (Tong et al., 2017). FA applies both diversification as well as intensification in search process (Johari et al., 2017). Diversification leads to generate diverse solutions exploring the search space globally; on the contrary intensification means concentration on small area in search space, i.e., local region which proves that current good solution is found in nearby region (Ritthipakdee et al., 2017). FA successfully applies exploration and exploitation (Louzazni et al., 2018). Randomness helps for exploration, helping not to stuck with any local optimum solution. Exploitation concentrates on finding solutions in neighbourhood where the optimality may be close, even if it is not global (Bidar et al., 2018; Lunrdi and Voos, 2018). Exploitation tends to use strong local information such as gradients, the shape of the mode such as convexity, and the history of the search process (Khan et al., 2018; Yelghi and Kose, 2018). The fogginess of the medium, the amount of attraction between fireflies and the amount of randomness all play a role in converging to optimum solutions (Elkhechafi et al., 2018a). It is now proven that FA is superior, when it comes to problems with many local optima (Ariyaratne et al., 2018; Elkhechafi et al., 2018b). When time is of the essence, the results are extremely fast (Najeeb and Dhannoon, 2018; Sakthidasan, 2014). As far as applying it to solving engineering problems, Gandomi et al. (2013) confirmed that FA can efficiently solve highly nonlinear, multimodal design problems. All these characteristics make FA distinctive from other techniques, so firefly has been selected in this research.

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PSEUDOCODE (Yang, 2009):
Objective function f(x), x = (x1, …, xd) T generate initial population of fireflies xi
(i = 1, 2, …, n)
Light intensity Ii at xi is determined by f(xi) Define light absorption coefficient
while (t < Max Generation)
For i = 1: n all n fireflies
For j = 1: i all n fireflies
    If (Ij > Ii), move firefly i towards j in d-dimension;
end if
Attractiveness varies with distance r via exp[−r]
Evaluate new solutions and update light intensity
    end for j
end for i
    Rank the fireflies and find the current best
end while
Post process results and visualisation
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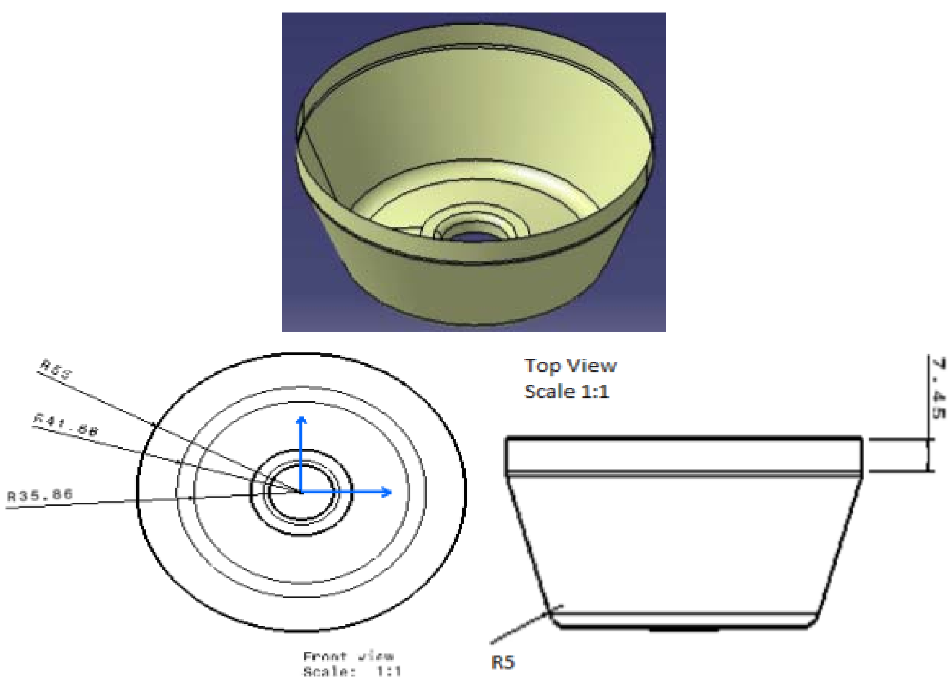
Figure 3 Production drawing of component (see online version for colours)



5 Component under study: tail cap

The component selected for fracture optimisation is tail cap. The component is manufactured by Vishwadeep Enterprises, Pune. The component is used in Tata Engineering & Locomotive Company Co. Ltd. The part no. of tail cap is 2779 4710 82 08. The weight of the original component is 20 grams. The thickness of the sheet selected is 1.2 mm. The material used is D 513, SS 4010. The yield strength of the material is 250 Mpa while the ultimate tensile strength was 350 Mpa. Figure 4 depicts solid model and production drawing of tail cap. Tail cap has complicate configuration that makes it difficult to draw. The walls have two regions, straight wall in upper portion and remaining area is convergent. The upper profile is circular and bottom is elliptical. The bottom with punched hole is not flat and has inclination. The configuration of component also plays major role in strain distribution.

Figure 4 Original tail cap design (see online version for colours)

6 Optimisation problem formulation

The optimisation problem was formulated by linear regression analysis based on research work carried out by Kakandikar (2014), the linear equations obtained were as follows

Minimise

$$\boldsymbol{fracture = 68925 - 294BHF - 64880\mu - 15515Rd - 1456Rp}$$

Subjected to

$$2 < Rd < 4, 3Rd > Rp > 6Rd$$

where

$$BHF = \pi / 4[d02 - (d1 + 2R)2] \times P$$

where

$$P = 2.5N / mm2 \text{ and } d1 \text{ ranges between } 108 \text{ to } 112$$

$$Rd = 0.035[50 + (d0 - d1)]\sqrt{S0}$$

where

Rd ranges in 2 to 4

where *d*0 is dependent on *d*1 and *S*0, *S*0 is sheet thickness. The problem was solved applying FA using MATLAB programming and the results are obtained (Ganesh and Vilas, 2016).

7 Results and discussion

Optimum geometry of component and process parameters have been arrived at by applying FA. Finite element analysis for formability of the original design with specified geometry and process parameters as received from manufacturer and for newly optimised geometry and process parameters with firefly optimisation for tail cap is carried out by using forming suite. Discretisation is shown in Figure 6 for optimised geometry. Figure 7 indicates the safety zone, slight wrinkling tendency is observed in upper flange, rest of the area is safe. Figure 8 indicates thickness distribution; few fracture points are observed around the hole in bottom, the flange indicated some accumulation of material termed as thickening. The flow of material from blank to drawn tail cap is represented in Figure 9. Figures 5 and 10 represent failure limit diagrams for both original and optimised components. The red points in figure represent failure points. Failure limit curve of original component shows many failure points as compared to that of optimum one. It clearly depicts that the failure points in optimised design have considerably reduced, which indicated that the design has been optimised and chances of failures have been minimised.

Figure 5 Forming limit diagram – original component (see online version for colours)

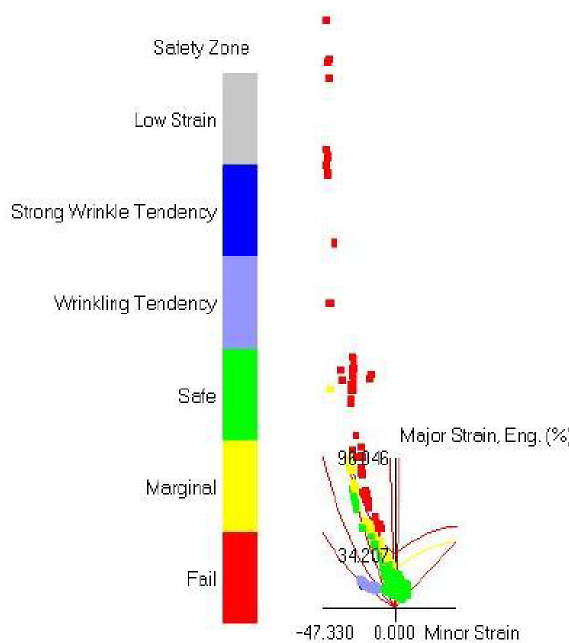


Figure 6 Meshing – optimised component (see online version for colours)

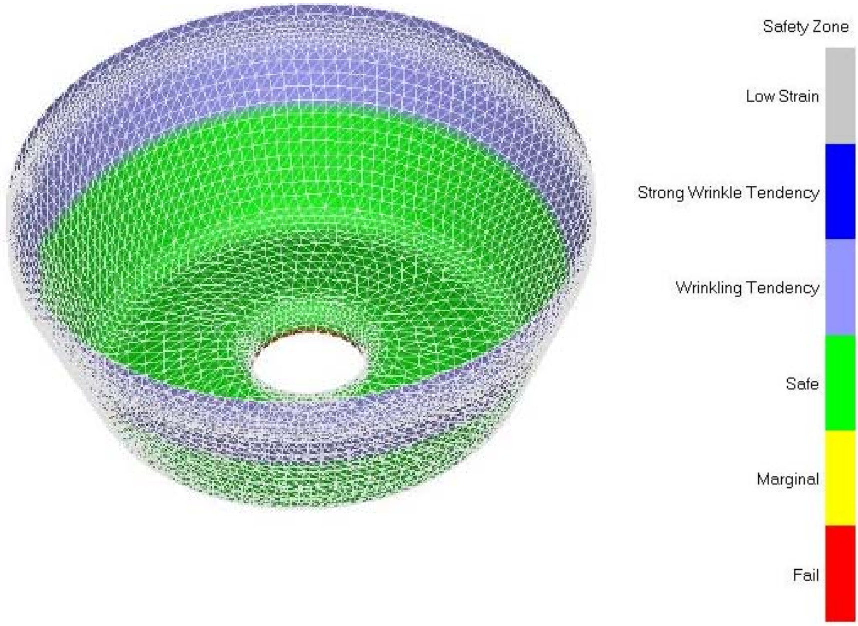
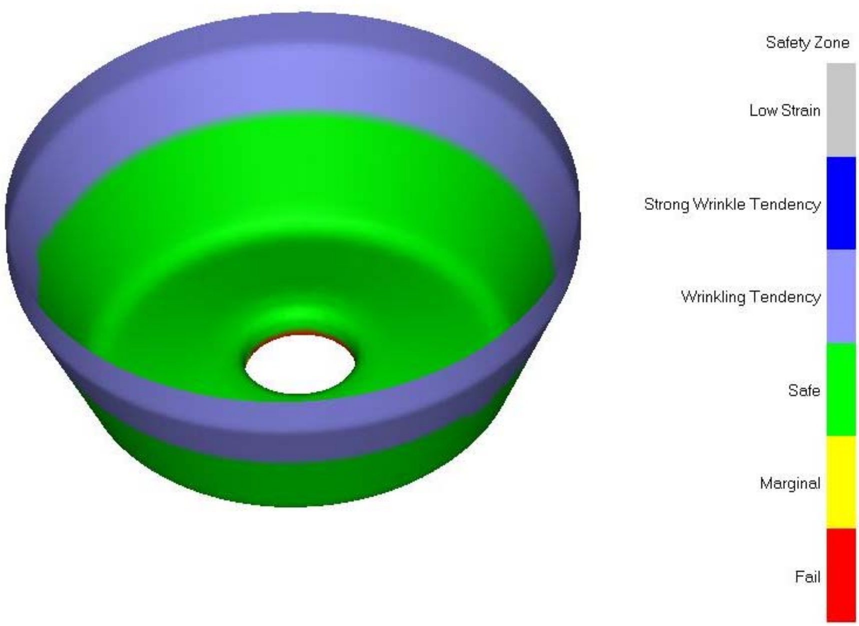


Figure 7 Safety zone – optimised component (see online version for colours)



Also figures indicate that the number of wrinkling points [violate] in the optimised component are reduced while the number of safe points [green] in the optimised component are increased. The marginal points [yellow] are also reduced in the optimised component as compared to the original component. Tables 1 and 2 presents process parameters; the fracture factor which is addition of square of distance of all fracture points from failure curve has been reduced from 36,854 to 24,332. Radius on die has been optimised as 3.70 mm from 3.90 mm. Optimum blank holder force achieved is 26.52 KN from that of 26.78 KN. Radius on punch in optimised design is 22.98 mm, and that of in original design was 23.41. The coefficient of friction has been optimised to 0.02 from that of 0.04.

Table 1 Results: original component

Fracture factor	36,854
Radius on die	3.90 mm
Blank holder force	26.78 KN
Radius on punch	23.41 mm
Coefficient of friction	0.04974

Table 2 Results: optimised component

Fracture factor	24,332
Radius on die	3.70 mm
Blank holder force	26.52 KN
Radius on punch	22.98 mm
Coefficient of friction	0.0215

Figure 8 Thickness distribution – optimised component (see online version for colours)

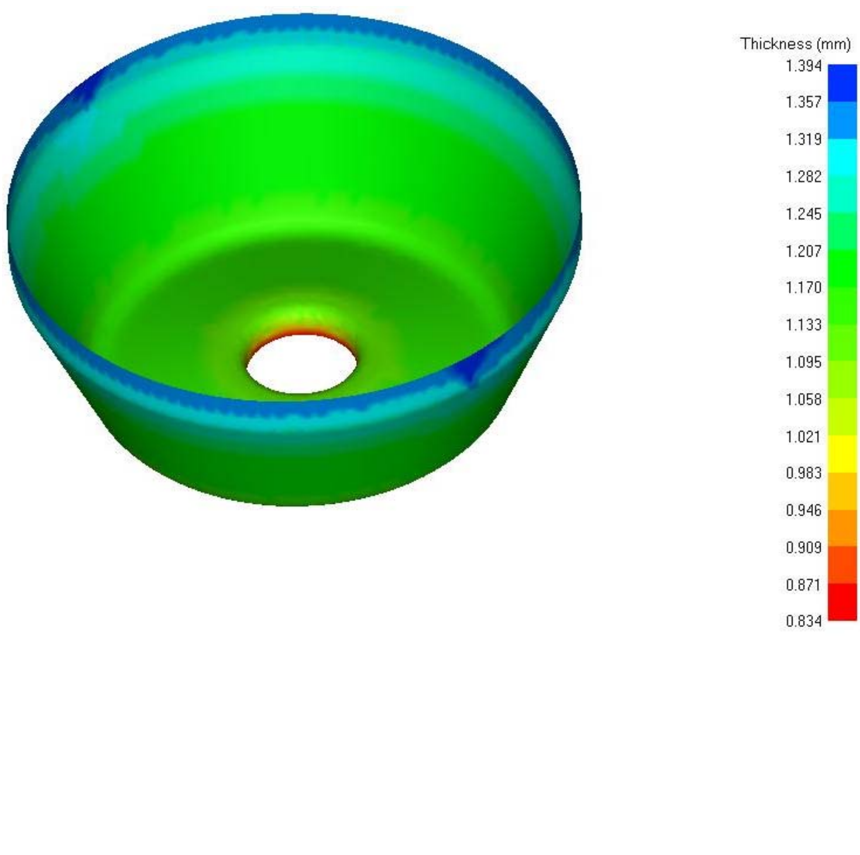


Figure 9 Material flow – optimised component (see online version for colours)

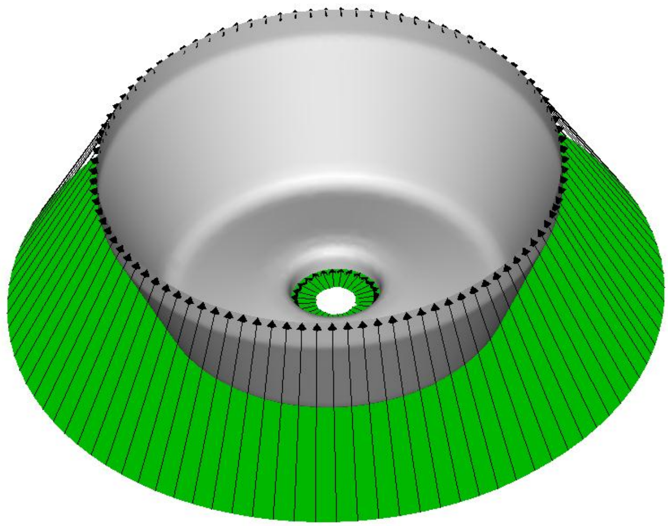
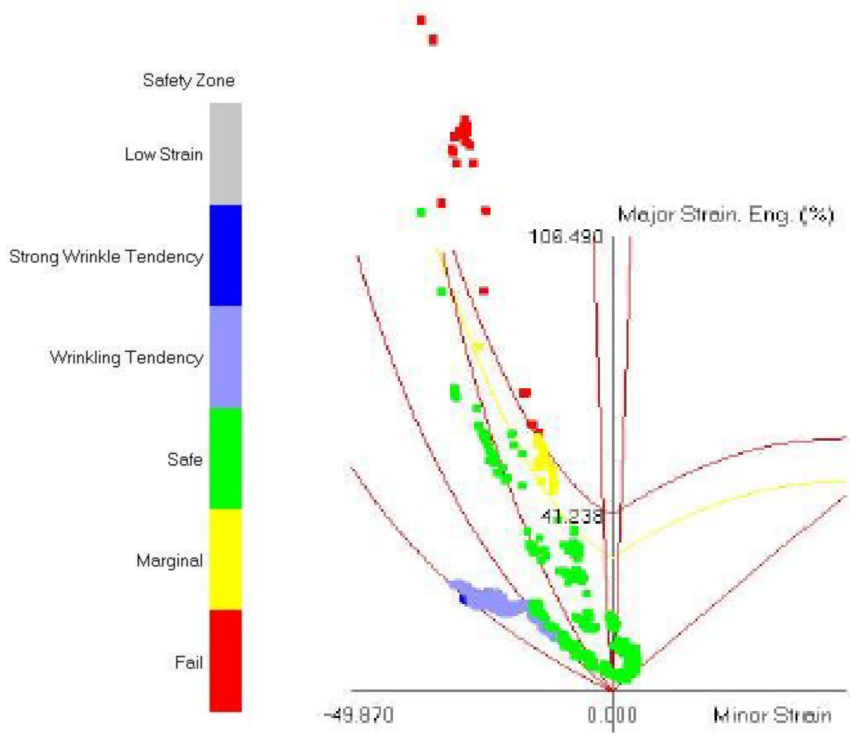


Figure 10 Forming limit diagram – optimised component (see online version for colours)



GA is one of the earliest and matured optimisation tool that was proposed in 1960 by John Holland. It works on the principle of natural genetics. It mimics the natural behaviour of survival for the fittest. The unfit population is removed over the generations and only suitable candidates are preserved, which are more competitive for solution (Goldberg, 2006).

PSO technique works on the principle of SI. The swarm of birds when flying towards food source has natural intelligence and every bird termed as particle adjusts his position with respect to the position of others. PSO technique involves simulating social behaviour among particles flying through a multidimensional search space, each particle representing a single intersection of all search dimensions. Particles can be seen as simple agents that fly through the search space and record and possibly communicate the best solution that they have discovered. The particles evaluate their positions relative to a goal (fitness) at every iteration and particles in a local neighbourhood share memories of their 'best' positions, and then use those memories to adjust their own velocities, and thus subsequent positions (Lee et al., 2018).

Table 3 Results: genetic algorithm

Fracture factor	30,349
Radius on die	3.75 mm
Blank holder force	26.32 KN
Radius on punch	23.10 mm
Coefficient of friction	0.040

Table 4 Results: particle swarm optimisation

Fracture factor	28,459
Radius on die	3.55 mm
Blank holder force	25.77 KN
Radius on punch	23.00 mm
Coefficient of friction	0.350

To validate the applicability and superiority of FA, results obtained are compared with that of achieved by applying GA and PSO as presented in Tables 3 and 4. The fracture factor given by GA is 30,349; by PSO is 28,459 whereas by firefly optimisation it is 24,332. It indicates highly optimised state, with reduction in fracture points.

From all these results and observations, it is concluded that in optimised design with FA fracture has been optimised.

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