ISSN XXXX XXXX © 2017 IJESC

Research Article Volume 7 Issue No.11

# Optimization of Sheet Metal Forming using Advanced Nature Inspired Algorithm

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**Abstract:**
It is recognized that fracture and wrinkling in sheet metal forming can be eliminated via an appropriate draw-bead design. Although deterministic multi objective optimization algorithms and finite element analysis (FEA) have been applied in this respect to improve formability and shorten design cycle, the design could become less meaningful or even unacceptable when considering practical variation in design variables and noises of system parameters. To tackle this problem, we present a multiobjective robust optimization methodology to address the effects of parametric uncertainties on draw-bead design, where the artificial bee colony optimization is developed. In this paper, the procedure of draw-bead design is divided into two stages: firstly, the data is trained using neural network and then the multiobjective artificial bee colony optimization, is used to optimize geometric parameters of draw-bead. The optimal output showed a good agreement with the physical draw-bead geometry and remarkably improve the formability and robust. Thus, the presented method provides an effective solution to geometric design of draw-bead for improving product quality.

**Keywords:** Artificial bee colony, Draw-bead, Fracture, Metal forming, Neural-network,

## I. INTRODUCTION

Engineering materials should be able to resist many forms of static or dynamic forces and arduous service conditions such as variable dynamic and static mechanical loadings, high operating temperatures, corrosion, etc [1]. The properties and structure of materials are interred related. The flow stress of metals at relatively low temperature is a function of the average grain size [2]. Cracking of materials can be avoided by the shape of structural elements [3].Sheet metal forming is one of the popular manufacturing processes in industries. The sheet metal operations are simple and cheap than forged operations [4]. Metal forming processes include a wide range of operations which deform sheet metal to form the component with the desired geometry [5]. Sheet metal is produced by rolling mills at low cost and high elastic modulus and high yield strength. Hence they are stiff and have a good strength-to weight ratio [6]. In complicated sheet metal formation improper design of process parameter will lead to fracture, wrinkling and spring back. To predict such defects and to avoid time consumption in trial and error tryout procedure, numerical simulation and optimization method have been separately applied [7].Numerical simulations of sheet metal plastic forming processes are becoming a common practice. Numerical analysis can provide in-depth look at the technological process and determine the optimal parameters [8] [9]. To perform optimization properly measurement analysis has to be done. Two major optical measuring technologies are digitizing by ATOS and forming analysis by ARGUS [10].The ATOS system is based on the triangulation principle. Forming analysis by ARGUS delivers the full distribution of major and minor strain, the thickness reduction [11]. The optimization problems optimize the maximum load required in formation. Genetic algorithm is used for the optimization purpose to minimize the load and to optimize the process parameters [12]. To improve the prediction efficacy Genetic Algorithm is combined with Artificial Neural Network [13]. Blank shape optimization method allows determination of a blank shape like edge geometry deviation of the produced product with respect to the specified product geometry [14] [15].Firefly can automatically sub-divide into sub groups and each group can potentially swarm around a local optimum and all optima can be obtained simultaneously if the number of fireflies is much higher than the number of modes. Hence firefly algorithm can handle multi model problems very efficiently due to this sub grouping ability [16].The Cuckoo Search algorithm is applied to the structural design optimization for solving structural design problems. Harmony Search is applied to some optimization problems in structural engineering. This algorithm initiates the design process by first selecting values randomly for joist and stringer sizes in each iteration. HS attempts to evolve the optimum dimensions for these members that will eventually result in minimum total cost [17]

## II. RELATED WORK

Zhihui Gong *et al.* [18] proposed to adopt a multi-objective particle swarm optimization with construction of a single cost function. MOPSO shows a certain advantage over other single cost function or population based algorithms. Radial basis function (RBF) was attempted to establish the metal models for fracture and wrinkling criteria in sheet metal forming design. A sophisticated automobile inner stamping case was demonstrated using RBF. This method provided better surrogate accuracy. This work improved the formability and can be recommended for sheet metal process design. Guangyong*et al.* [19] presented a variable fidelity algorithm which integrates the one step solver with incremental solver for optimizing sheet metal forming process. By predefining the experimental points and constructing a corrected function the difference between two solvers was determined. Surrogate models for compensating the responses of the one step solver at other points were evolved. The compensated low fidelity model can be used as a high fidelity model in the optimization process. Artificial bee colony (ABC) algorithm was used to obtain the global optimum. The optimal design of draw-bead restraining forces for an automobile inner panel was exemplified to demonstrate the capability of the variable fidelity method combined with the ABC algorithm. They showed that the optimization with variable fidelity method improved the computational efficiency and formability of the work piece. Wiebenga*et al.* [20] analyzed the robustness of a sheet metal forming process using finite element (FE) simulations. They presented a pragmatic, accurate and economic approach to measure and model one of the main inputs. They combined mechanical testing and texture analysis to limit the required effort. To efficiently model the material property scatter for use in the numerical robustness analysis the correlations between material parameters was calculated. The proposed approach is validated by the forming of a series of cup products using the collected material.

The observed experimental scatter can be reproduced efficiently using FE simulations, demonstrating the potential of the modeling approach and robustness analysis in general. Guenhael*et al.* [21] represented the post-spring back shape by a level set function. They designed stamping processes which include the geometry of the tools, the shape of the initial sheet blank, the material constitutive law and the process parameters. Reduced order shape space evolved by extending shape manifold approach to spring back assessment for 3D shapes. Then an optimization algorithm designed to minimize the gap between the post-springback and the desired final shapes was proposed. The desired level set functions were generated from a corresponding set of spring back shapes predicted by Finite Element simulations. The minimal number of parameters needed in order to uniquely characterize the final formed shape regardless of complexity was designed. Lanouar*et al.* [22] presented a finite element approach for numerical simulation of the incremental sheet metal forming. The goal was to develop a simplified FE model to simulate the ISF process. In order to predict nodes in contact with the tool, a simplified contact procedure was proposed. They have estimated the imposed displacements also.

An elasto-plastic constitutive model with isotropic hardening behavior and a static scheme was adopted to solve the nonlinear equilibrium equations. El Salhi*et al.* [23] presented a 3D surface mechanism to support the generation and application of classification techniques. Different mechanisms for prediction (classification) techniques were Local Geome try Matrices (LGMs), Local Distance Measure (LDM), and Point Series (PS). The representations were designed to capture the nature of 3D surfaces in terms of their local geometry and predict class labels associated with such local geometries. Spring-back was a form of deformation that occurs across a manufactured 3D surface as a result of the application of some sheet metal forming process

**III. PROPOSED METHODOLOGY**

This paper aims to address the issues of nondeterministic design for sheeting metal forming process. An effective multi-objective robust optimization method will be developed and applied to a real-life draw-bead design based on dual response surface models. To deal with this problem, the design procedure is divided into two stages such as: firstly, the optimal equivalent draw-bead restraining forces are obtained through a neural network by training the data; and secondly, the equivalent restraining force


**Figure.1. Fracture and Wrinkling faults in the forming process**

To develop multi objective robust optimization for sheet metal forming, we firstly establish the objective functions with respect to the draw-bead forces by using a dual response surface approach, one for mean and another for standard deviation in each objective. Following this, a multi-objective ABC procedure is applied to optimize the draw bead forces. Then, a single-objective ABC optimization is carried out to inversely determine the geometric parameters of draw-bead for generating the desirable optimal draw-bead forces. This section will introduce these relevant methods.

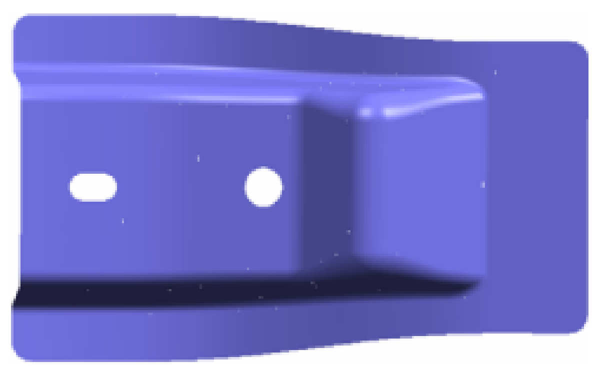


**Figure.2. Automobile inner panel**

In general, the further the distance from the safety zone, the higher the risk of wrinkling and or rupture. In order to quantify different extent of crack and wrinkling in terms of the distance to the safety zone in the forming limit diagram, an exponential weight criterion is presented. Therefore, the rupture and wrinkling objective functions can be formulated, respectively, as:

$$W(\varepsilon_2) = -\varepsilon_2 \qquad (1)$$

$$\eta(\varepsilon_2^e) = -\tan(45^\circ + \theta)\varepsilon_2 \qquad (2)$$

Where h is a user chosen ‘‘safety” marginal angle in WLC. When the major principal strain e1 locates in the safety zone, the rupture and wrinkling values go to zero. When e1 is beyond the safety zone, there is a risk of rupture and/or wrinkling. In general, the further the distance from the safety zone, the higher the risk of wrinkling and/ or rupture. Therefore, the rupture and wrinkling objective functions can be formulated, respectively, as:

$$R_{obj} = \sum_{e=1}^{N} [\varepsilon_1^e - \varphi(\varepsilon_2^e)] \exp[\varepsilon_1^e - \varphi(\varepsilon_2^e)] \quad \varepsilon_1^e \geq \varphi(\varepsilon_2^e) \qquad (3)$$

$$W_{obj} = \sum_{e=1}^{N} [\eta(\varepsilon_2^e) - \varepsilon_1^e] \exp[\eta(\varepsilon_2^e) - \varepsilon_1^e] \quad \varepsilon_1^e \leq \eta(\varepsilon_2^e) \qquad (4)$$

### 3.1 NEURAL NETWORK FOR TRAINING THE DATA

An artificial neural network (ANN) is a computational model which works on the basis of structure and functions of biological neural networks. The neural network learning procedure changes based on the input and output which affects the information that flows through the network. These networks were considered as a nonlinear statistical data modeling tools. Complex relationships between inputs and outputs were modeled which leads to the formation of patterns. The Proposed ANN method is trained using feed forward neural network. In feed forward neural network connections between the units do not form a directed cycle. Here the information moves in only one direction. There are no cycles or loops in the network. The ANN consists of three layers: input, output and hidden layer. They are composed of a series of computational node structured into several layers. Each node is connected to all the nodes in the previous layer.

**Table.1. Dataset Used For Training by Neural Network**

| | Design variables | | | | Noise Factors | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | j | 0.13 | | | 0.14 | | | 0.16 | | | 0.17 | |
| | | | | | m | 0.27 | | | 0.30 | | | 0.26 | | | 0.29 | |
| | | | | | b | 2.15 | | | 2.09 | | | 2.02 | | | 2.22 | |
| | | | | | No. | 1 | | | 2 | | | 3 | | | 4 | |
| No. | $Db_1$ | $Db_2$ | $Db_3$ | | | $R_{obj}$ | $W_{obj}$ | | $R_{obj}$ | $W_{obj}$ | | $R_{obj}$ | $W_{obj}$ | | $R_{obj}$ | $W_{obj}$ |
| 1 | 80.00 | 142.86 | 125.71 | | | 6.36 | 8.79 | | 6.33 | 8.63 | | 7.29 | 7.92 | | 7.46 | 7.20 |
| 2 | 85.71 | 108.57 | 177.14 | | | 6.00 | 8.72 | | 6.00 | 8.75 | | 6.00 | 7.89 | | 6.15 | 7.13 |
| 3 | 91.43 | 85.71 | 148.57 | | | 6.00 | 9.35 | | 6.00 | 9.24 | | 6.00 | 8.16 | | 6.04 | 7.60 |
| 4 | 97.14 | 160.00 | 182.86 | | | 7.27 | 7.19 | | 7.57 | 7.17 | | 8.43 | 6.48 | | 8.45 | 5.66 |
| 5 | 102.86 | 114.29 | 131.43 | | | 6.00 | 8.07 | | 6.00 | 8.13 | | 6.00 | 7.11 | | 6.26 | 6.39 |
| 6 | 108.57 | 131.43 | 194.29 | | | 6.00 | 6.91 | | 6.00 | 7.09 | | 6.28 | 6.21 | | 6.75 | 5.63 |
| 7 | 114.29 | 102.86 | 188.57 | | | 6.08 | 7.43 | | 6.00 | 7.49 | | 6.08 | 6.87 | | 6.33 | 6.25 |
| 8 | 120.00 | 148.57 | 137.14 | | | 6.66 | 6.49 | | 6.41 | 6.41 | | 7.34 | 5.83 | | 7.93 | 5.20 |
| 9 | 125.71 | 80.00 | 165.71 | | | 6.13 | 8.22 | | 6.02 | 8.21 | | 6.30 | 7.37 | | 6.90 | 6.70 |
| 10 | 131.43 | 125.71 | 154.29 | | | 6.33 | 6.49 | | 6.03 | 6.50 | | 6.39 | 5.84 | | 7.26 | 5.30 |
| 11 | 137.14 | 97.14 | 120.00 | | | 6.37 | 7.54 | | 6.21 | 7.48 | | 6.76 | 6.75 | | 7.47 | 6.07 |
| 12 | 142.86 | 154.29 | 160.00 | | | 7.20 | 5.58 | | 6.88 | 5.59 | | 8.48 | 5.09 | | 9.22 | 4.45 |
| 13 | 148.57 | 120.00 | 200.00 | | | 7.61 | 6.15 | | 6.72 | 6.19 | | 7.27 | 5.56 | | 8.13 | 6.19 |
| 14 | 154.29 | 137.14 | 142.86 | | | 7.35 | 5.65 | | 6.90 | 5.72 | | 8.02 | 5.10 | | 8.87 | 4.48 |
| 15 | 160.00 | 91.43 | 171.43 | | | 8.46 | 6.81 | | 8.79 | 6.77 | | 9.14 | 6.12 | | 9.89 | 5.55 |

layer. They are composed of a series of computational node structured into several layers. Each node is connected to all the nodes in the previous layer.

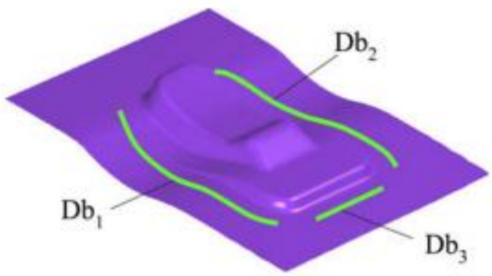



**Figure.3. Outline of Draw-Bead**

Let $\{x_i\}$ be the input where $1 \le i \le n$ and y be the output variable. The generalized model of the neural network can be given as Y for output of the entire network and H for output at the hidden layer. Let $x_0$ be the input carrying the constant value which acts as bias. The output from the input layer has weight $W_{ih}$ where i represent the input node and h represents the hidden node. The output at the hidden layer has basis function and activation function. The basis function is given as

$$b_h = x_0 + \sum_{i=1}^{N} x_i w_{ih} \qquad (5)$$

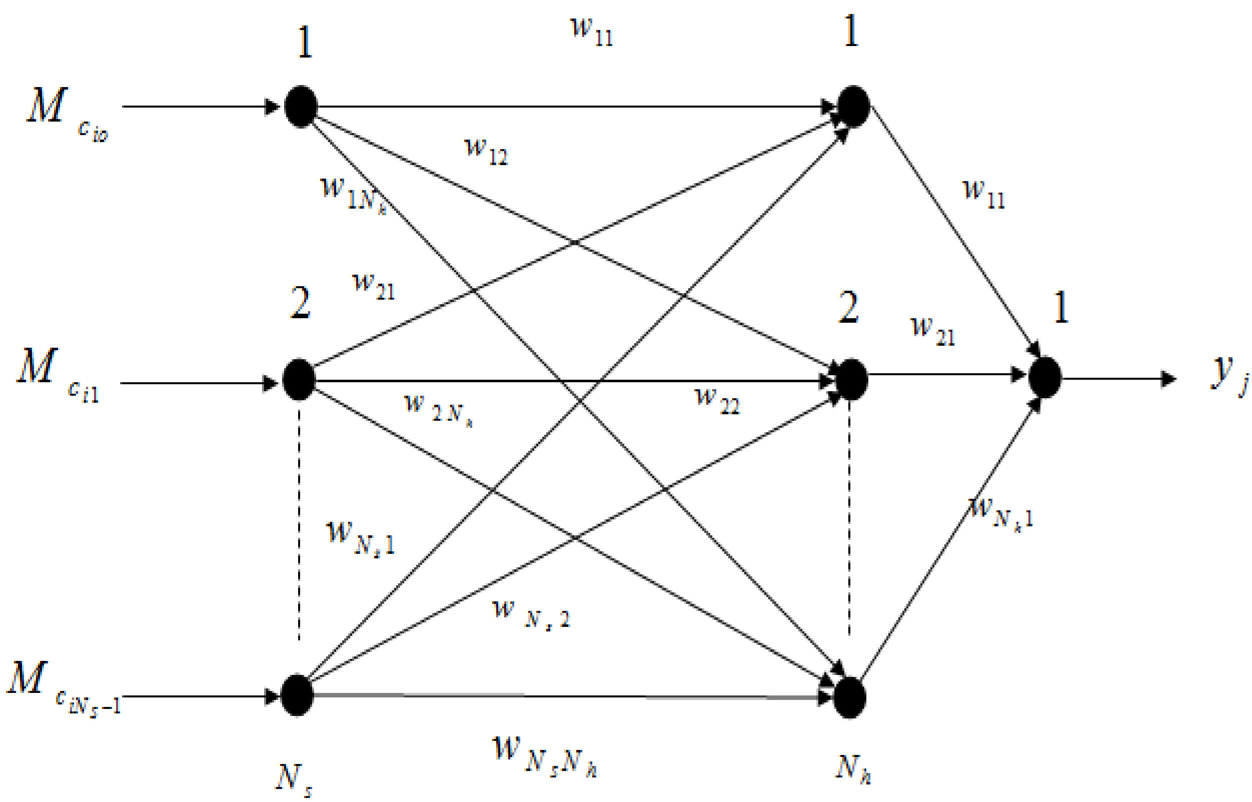



**Figure.4. N Inputs and One Output Neural Network to Train the Dataset**

The activation function which is the output of the hidden layer is given as

$$H = \frac{1}{(1+e^{-b_h})} \qquad (6)$$

The output at the output layer also has basis function and activation function. The basis function is given as

$$b_o = x_0 + \sum_{i=1}^{N} H w_h \qquad (7)$$

Where

$W_h$ represents the weight at the hidden layer.

The activation function at the output layer acts as the output of the whole model.

$$Y = \frac{1}{(1+e^{-b_o})} \qquad (8)$$

The final trained dataset is used for the proposed optimization process. Here artificial bee colony is used for optimization of draw beads Db1, Db2and Db3 under 3 different cases

### 3.2 ARTIFICIAL BEE COLONY ALGORITHM

It is a robust, simple and population based stochastic optimization algorithm. This optimization, which performs based on a particular intelligent behavior of honeybee swarms, is easy to implement. The colony consists of three groups of bees.

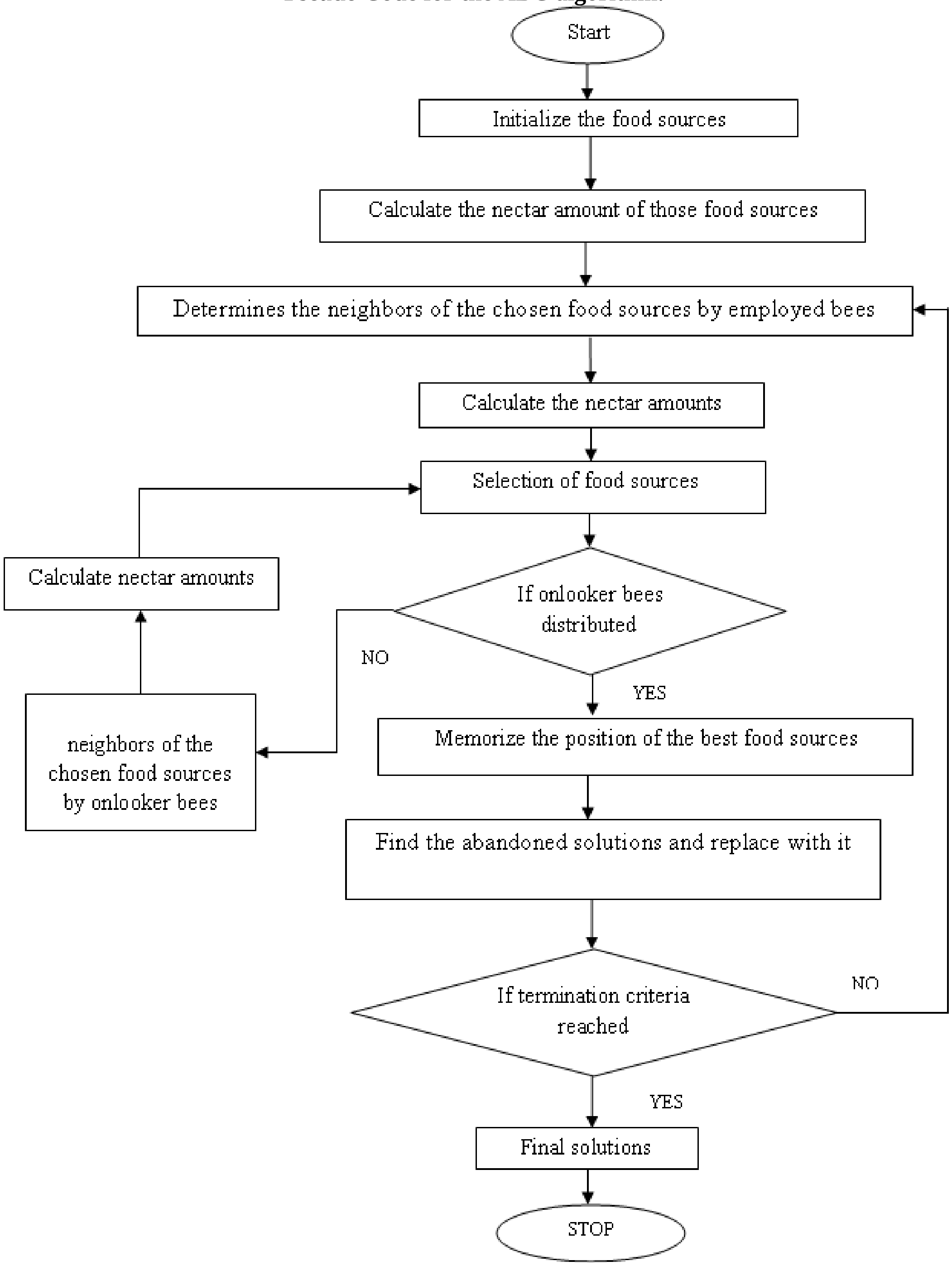
i. Employed bees
ii. Onlooker bees
iii. Scout bees

The number of food sources is equal to the number of employed bees and onlooker bees in the hive. In the proposed system, multi objective functions are used. The steps of the artificial bee colony algorithm are given below in detail. *Initialize* the population of the food sources. The initial food sources are selected randomly in this work. The employed bees are allocated depends on the food sources

***REPEAT: Employed bees***

Employed bees are assigned to go to the food sources and determine the neighborhood food sources in the search

**Pseudo Code for the ABC algorithm:**




***Onlooker bees:***

Every on looker bee is used to watch the dance of the employed bees. Based on its dance, it can select the better sources and it will go to that sources and chooses the neighborhood sources around that. Now onlooker bees evaluate the nectar amount.

***Scout Bees:*** Bees used to select the abandoned food sources and replace those sources by new food sources are called as Scout bees. *Memorize* the best solution achieved so far *UNTIL* the requirements are met the optimum dimension set is determined using the implementation of the above optimization algorithm in the platform of MATLAB. The flow chart explains the processing of the artificial bee colony algorithm in our proposed system. It is given below in detail.

## 4. EXPERIMENTAL SETUP

The proposed technique is implemented in a system having 8 GB RAM with 32 bit operating system having i5 Processor using MATLAB Version 2014. Here for finding the efficiency and to minimize the error we used certain parameters and it is discussed briefly

### 4.1 RESULTS AND DISCUSSION

In this graph, we find the performance of the fitness value of proposed and existing method. While comparing with the existing method, the proposed method shows better performance. Here the proposed method ABC is compared with the existing method PSO. In this graph, if the iteration value is 10, then the fitness value is around 16.5 for both

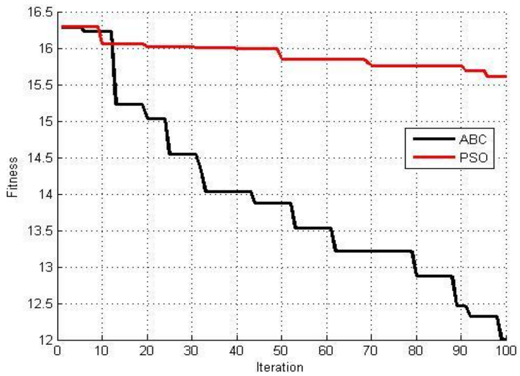



**Table.2. Proposed Method**

| | Db1 | Db2 | Db3 | Robj | Wobj |
|---|---|---|---|---|---|
| Case1 | 160 | 160 | 184.4627 | 7.458886 | 4.546137 |
| case2 | 152.1251 | 149.6334 | 181.2801 | 7.033302 | 4.374613 |
| case3 | 123.5608 | 128.7345 | 175.182 | 5.804768 | 5.889815 |
| case4 | 112.2436 | 114.2214 | 183.1695 | 6.203855 | 6.009562 |

**Table.3. Existing Method**

| | **Db1** | **Db2** | **Db3** | **Robj** | **Wobj** |
|---|---|---|---|---|---|
| **Case 1** | 85.37363 | 135.6043 | 167.0512 | 6.554108 | 9.051389 |
| **case2** | 133.2924 | 91.69007 | 191.7127 | 7.132436 | 7.499942 |
| **case3** | 80.86094 | 141.1452 | 175.958 | 6.492351 | 7.779971 |
| **case4** | 80.0141 | 156.3085 | 145.0041 | 8.214223 | 6.864437 |

In this table it contains four cases and three inputs (Db1, Db2, and Db3). For each case the input value get change and for that input value we contain different Robj and Wobj value. In this existing method the value of input is higher and reaches maximum value in Robj and Wobj, so the performance is not good. While compare with existing method the proposed achieves minimum Robj and Wobj value. The proposed method is better than the existing method and shows better performance.

## 5. CONCLUSION

Fracture and wrinkling are predominant defects in sheet metal forming process. The existence of these defects may damage surface quality, reduce dimensional precision, cause local crack of component and lead directly to waster. In order to improve product quality and reduce cost, various optimization techniques have been successfully applied to sheet metal forming process. However, traditional optimization has focused on deterministic and or single robust objective. Real-life engineering problems are typically nondeterministic and come with multiple objectives. In this paper, the rupture and wrinkling criteria based on exponential weight are adopted in the draw bead design for the sheet metal forming, and an optimization methodology is shown. The design procedure is integrated with neural network and the ABC optimization for optimizing geometric parameters of draw bead. Hence the proposed method justified that the proposed method effectively improved in the end after comparing with the existing techniques for geometric design of draw bead for improving product quality.

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