

Intelligent die design optimization using enhanced differential evolution and response surface methodology

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Abstract Die design process is one of the most complex production design phases in the automotive manufacturing sector and it is the primary and important factor that affects the product development performance. The goal of this research is to describe how to use intelligent die design based on shape and topology optimization using a new improved differential evolution algorithm and response surface methodology. In the simulation process, not only die deflection, but also press table deflection is taken into account in order to achieve more realistic results. The validation of the present approach is evaluated by a comparison of experimental test and simulation results. The optimal shape parameters for the die structure were obtained using response surface methodology and new improved optimization algorithm. In the optimization phase differential evolution was handled and improved with a new mutation strategy which uses the best vectors in the population as differential vectors was developed and used in the new developed algorithm (DEBVs). With the developed DEBVs algorithm better results with less function evaluation numbers were handled. By using this intelligent methodology in the design stage of die, significant results were obtained: the mass was reduced approximately 24 % and the current maximum stress decreased approximately 72 %.

Keywords Sheet metal forming · Intelligent die design · Optimization · Differential evolution · Response surface

Introduction

Sheet metal stamping process is one of the base production methods in automotive industry. The fundamental component of sheet metal process is the die. Designing dies in shorter time have a key role in the product development process. In a vehicle designing and manufacturing process the cost of a die has an important percentage in the total cost of a vehicle. This cost has a very important role for an automotive company to compete with other companies. In order to decrease this cost total manufacturability must be taken care of. With considering total manufacturability, also the quality of stamping process is enhanced. At this point two important factors must be taken care of; improving the structure integrity of dies and decreasing the weight of dies. Traditional die design techniques following some design standards evolved by designer experiences over years remain incapable in order to meet these two requirements. Besides, these standards doesn't have any flexibility for new designs and design changes. Further, stoppage of the entire assembly line due to the breakage of the die, affects the total cost directly. For this reason beyond the standard techniques, innovative techniques must be implemented to the die design process in order to design more robust dies. Building heavy dies due to the robustness and conservative standards causes incremental of material, construction and electrical costs.

Structural analyses of dies have been used for both calculating the design changes of existing dies and the forming loads of new designs. By using structural analyses the cost of dies has been decreased considerably. To predict the structural behavior of dies has an important issue for the design

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stage. Research on the deformation of dies and on the springback effect during sheet metal forming has been conducted widely by researchers; however, only a few of them have been interested in the die deformation process and optimization of the die structure. [Elkins and Sturges \(1996\)](#) developed a new method for controlling the springback effect happens in the bending processes. The method utilizes a knowledge of each workpiece's individual strength and thickness characteristics for controlling the bending process and uses simple measurements of material properties to provide the information necessary to estimate springback. Finite element-based simulation approaches are often used under the assumption that the dies and tools are rigid. [Tekkaya \(2000\)](#) discusses numerical simulations in the sheet metal forming industry and possible developments. He has given a comparison between bulk and sheet metal forming processes from the simulation point of view and he has emphasized on the static explicit and dynamic implicit finite element procedures.

Intelligent systems pertaining to sheet metal parts and die design processes have been used successfully in recent years. [Vosniakos et al. \(2005\)](#) developed an intelligent system for a sheet metal part and process design that stores knowledge and prescribes ways to use this knowledge according to the programming in logic paradigm. In some cases uncertainty problems come up in the complex die design stage have been solved by using fuzzy set theory. [Lin and Chang \(1994\)](#) used fuzzy set theory in the die design process to find out the definite design attributes by categorizing and managing the uncertainty design parameters. [Garcia \(2005\)](#) designed an integrated automatic control algorithm uses sensors, artificial vision, and neural networks based on fuzzy logic for the diagnosis and the prediction of any disturbance in sheet metal forming process.

The expectation of carrying out the production in minimum cost and maximum quality has expanded with the raising customer satisfaction. In order to meet this expectation, the necessity of using optimization methods has increased especially in making brand new designs and solving problems appeared. In recent years, the use of simulation in die design process has increased significantly to prevent costly shop trials. Topology design searches for the best conceptual die structure on a predefined design domain. By coupling the simulation and topology design, optimal die design structure is defined at the early stages of the die design to produce high quality car bodies with reduced development time and cost. The researcher who generates the design or tries to solve the problems appear during the die design process needs a reliable and efficient optimization algorithm when solving the optimization problems appeared. [Sun et al. \(2011\)](#) proposed a multi-objective particle swarm optimization for fracture and wrinkling criteria in sheet metal forming design. [Liew et al. \(2004\)](#) presented an evolutionary algorithm that is capa-

ble of handling a relatively simple springback minimization process design optimization problem. In this respect, [Hou et al. \(2010\)](#) proposed a stochastic analysis and an optimization approach where finite element simulation and response surface methodology are used to construct a meta-model based on which Monte–Carlo simulation is performed to predict the quality of input parameters of a deck lid inner panel stamping. [Muhammad et al. \(2012\)](#) used response surface methodology to develop a mathematical model for predicting the weld zone development problem and they investigated the effect of parameters in resistance spot welding on the problem using Taguchi method. [Chiu et al. \(2012\)](#) designed a radial basis function neural network for time series forecasting using both an adaptive learning algorithm and response surface methodology. They used response surface to determine the network parameter values and formulate improved design criteria for neural networks. [Lu et al. \(2011\)](#) developed direct search methods for die shape optimization problems and evaluated the efficiency and robustness of these methods for net-shape forming problems. They evaluated three different types of direct search methods (a modified simplex method, a random direction search and an enhanced Powell's method) to explore the simplicity and flexibility. They developed a new localised response surface method combining linear response surface approximation and direct search for minimization of the objective function to improve the robustness.

[Storn and Price \(1995\)](#) developed a new robust, versatile and easy to use global optimization algorithm and published it with the name differential evolution (DE) algorithm in 1995. Since then researches have been trying to enhance the algorithm with their own original inspirations. DE was used in solving various optimization problems occurring in mechanical systems, aerodynamics and aeronautics, control algorithms of various systems, agriculture and etc. Except the developers of DE algorithm, the performance of DE has been evaluated firstly by [Brutovsky et al. \(1995\)](#) using 15 test functions. [Montes et al. \(2005\)](#) developed a differential evolution algorithm containing a diversity mechanism for solving the constrained optimization problems. They tested the algorithm performance by solving 13 different test functions found in the literature. [Chakaravarthy et al. \(2012\)](#) developed a DE–PSO (Partial Swarm Optimization) algorithm for solving m-machine flow shops with lot streaming to minimize the makespan, total flow time of all jobs in a flow shop and found better and optimal solution for the optimization problem. [Vincent et al. \(2012\)](#) employed four variants of DE (DE/rand/1/bin, DE/targetto-best/1, DE/best/1/bin, and DE/best/2) to schedule three kinds of flexible assembly line scheduling problems. Besides they developed a metaheuristic algorithm to solve these problems by optimizing two processes: the assignment of operations to workstations and the timing and sequence in which the orders are processed.

They found promising results in terms of higher mean fitness and fast convergence speed using bi-level DE algorithms.

Shi et. al. proposed a comprehensive approach to make die shape optimization for sheet metal forming processes by maximizing the stamping quality at the same time minimizing the risk of rupture, wrinkles and unstretched areas on the sheet metal part. Xu et al. (2012) proposed a topology optimization methodology for advanced high strength steels stamping die. They took into account the interaction behavior of tools during stamping process simulation modeling in order to obtain more accurate boundary force condition for die structure optimization.

In this study, it is aimed to develop a new algorithm that is user-friendly, global, reliable in converging the real optimum value and also consuming as short time as possible from the beginning to the end of the optimization process in the die design process. A simulation and topology based die structure design approach with differential evolution using the best vectors (DEBVs) is presented for sheet metal stamping process in the automotive industry. Differential evolution was handled and improved with a new mutation strategy which uses the best vectors in the population as differential vectors was developed and used in the new developed algorithm (DEBVs) in the optimization process. Constraint test problems which were frequently used as a test tool for many new algorithms were solved with the developed DEBVs algorithm and better results with less function evaluation numbers were handled when comparing the results of other algorithms. The approach is validated through physical tests applied to an example die for a vehicle body part. A comparison between numerical simulation results and measurements showed that the present approach is quite acceptable for use as a design frame tool at the early stages of die design. The developed algorithm can be very helpful as an assistant tool for engineers during vehicle die design and manufacturing process in terms of time, cost, quality and convenience.

The goal of this research is to describe how to use intelligent die design based on shape and topology optimization using enhanced differential evolution and response surface methodology. With the developed DEBVs algorithm better results with less function evaluation numbers were handled. By using this intelligent methodology in the design stage of die, significant results were obtained: the mass was reduced approximately 24 % and the current maximum stress decreased approximately 72 %. Using this methodology in the design stage of die and sheet metal stamping, major improvements to the vehicle development process can be made, such as reducing the weight and the cost of die, reducing the labor costs during pattern practice and reducing the environmental damage or CO₂ emissions by reducing the amount of cast iron.

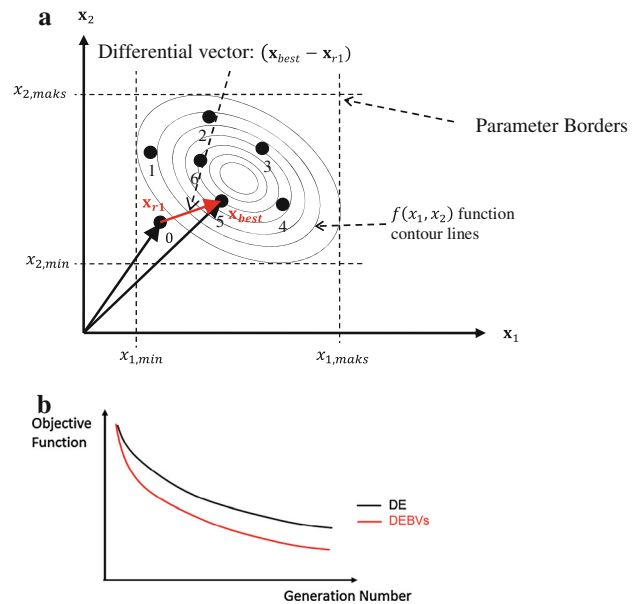


Fig. 1 a Differential vector in the developed DEBVs algorithm, b the convergence speeds of DEBVs and DE

Differential evolution using the best vectors (DEBVs)

Storn and Price (1995), developed a new robust, versatile and easy to use global optimization algorithm and published it with the name differential evolution (DE) algorithm in 1995. This algorithm like other evolutionary algorithms (EAs) has a population-based structure and it attacks the starting point problem using real-coded system. In this study a new differential mutation strategy using the best vectors in the population (DEBVs) was developed. With developed algorithm the global optimum point was reached at reduced function evaluations and the best results were handled with the same function evaluation numbers.

Here the new developed mutation strategy has a key role shown in Fig. 1a. The properties of population (initial population, crossover and reproduction) are the same as in the other evolutionary algorithms. In the developed algorithm differential vector is created from the best vectors in the population. But every generation the random vector and the best vector are replaced between each other (Fig. 1a).

Developed DEBVs algorithm is created the population around the global optimum point from the first generation. This property is the distinctive property of DEBVs with regards to the performance criterion. When using developed DEBVs algorithm for solving different test functions, DEBVs converges to the global optimum points faster than DE and at the same generation numbers DEBVs gives better results (Fig. 1b).

DEBVs algorithm like other evolutionary algorithms (EAs) has a population-based structure and it attacks the

starting point problem using real-coded system and a new differential mutation operator. DEBVs consists of two fundamental phases: initialization and evolution (Karen 2011). In the initialization phase just like in other evolutionary algorithms, an initial population (\mathbf{P}^0) is generated. After that \mathbf{P}^0 population evolves to \mathbf{P}^1 , \mathbf{P}^1 evolves to \mathbf{P}^2 . In this way evolution of new populations is continued until termination conditions are fulfilled. While evolving from \mathbf{P}^n population to \mathbf{P}^{n+1} population three evolutionary operations are executed to the individuals in the current population. These operations are; *differential mutation, crossover and selection*.

Initial population \mathbf{P}^0 is created from N_p number of individuals randomly:

$$x_j^{0,i} = b_j^L + \alpha_j^i (b_j^U - b_j^L), 1 \leq j \leq N \quad (1)$$

where 0 means initial population, i is the sequence of population, j is the number of individuals in the population, α_j^i is the real random number generator in the i th population and j th individual. b_j^L is the lower value of j th individual and b_j^U is the upper value of j th individual.

In mutation a mutant ($\mathbf{v}^{n+1,i}$) and a mutant vector ($\mathbf{x}^{n+1,v,i}$) is created for each $\mathbf{p}^{n,i}$ individual called mother in \mathbf{P}^n population. It should not be forgotten that \mathbf{x} is a vector which represents all individuals in the current population ($\mathbf{x} = x_1, x_2, \dots, x_N$). Mutant vector $\mathbf{x}^{n+1,v,i}$ is created by two different formulations as follows:

$$\begin{aligned} \text{First formulation: } \mathbf{x}^{n+1,v,i} &= \mathbf{x}^{n,best,i} \\ &+ \sum_{y \geq 1} F_y (\mathbf{x}^{n,p_{1y}} - \mathbf{x}^{n,best,i}), \\ \text{Second formulation: } \mathbf{x}^{n+1,v,i} &= \mathbf{x}^{n,best,i} \\ &+ \sum_{y \geq 1} F_y (\mathbf{x}^{n,best,i} - \mathbf{x}^{n,p_{2y}}), \\ 1 \leq i \neq p_{1y} \neq p_{2y} &\leq N_p \end{aligned} \quad (2)$$

where $\mathbf{x}^{n,best,i}$ is the best vector (*best*) selected for the new individual that will be created for i th old individual in n th population, $\mathbf{x}^{n,p_{1y}}$ is the P_{1y} th individual selected randomly from between $[1, N_p]$ integers, similarly $\mathbf{x}^{n,p_{2y}}$ is the P_{2y} th individual selected randomly from between $[1, N_p]$ integers, F_y is the scale factor for y th vector difference in the range of $[0,1]$.

In the crossover process a new child individual ($\mathbf{c}^{n+1,i}$) is created by mating the new individual ($\mathbf{x}^{n+1,i}$) which is created in the mutation process with the current individual ($\mathbf{p}^{n,i}$) in the population according to the crossover probability C_r . Here $\mathbf{p}^{n,i}$ is referred to as mother and $\mathbf{x}^{n+1,i}$ is referred to as father (Fig. 2).

There is a competition between mother and child in the selection operation. They compete with each other according to objective function values to survive in the next generation

(Karen 2011). This competition is formulated mathematically as follows;

$$\mathbf{p}^{n+1,i} = \begin{cases} \mathbf{c}^{n+1,i}, & \text{if } (\mathbf{c}^{n+1,i} > \mathbf{p}^{n,i}) \\ \mathbf{p}^{n,i}, & \text{otherwise} \end{cases} \quad (3)$$

Equation (1) is used for creating the initial population, Eq. (2) is used for creating the mutant vector in DEBVs algorithm and Eq. (3) is used for the selection stage of proposed algorithm in the following engineering problems and in the die design optimization problem.

Die design phase, simulation, physical tests and correlation

In this research, first, the solid models of dies were defined using computer-aided tools. Then, finite element codes for the parts including boundary conditions and loads were designed. Although many researchers have used finite element codes for simulation of the die design process, significant consideration is given to defining the simulation model and the boundary conditions and to defining test procedures to verify the simulation technique in this research. Test procedures were defined, and test tools, such as a 16-channel data acquisition unit, are used to measure displacements. Then, experimental and numerical results were compared to evaluate the process conditions and to check the correlation of the results. Very good correlation was obtained between the test and simulation results (Karen et al. 2012).

Design performance is highly dependent on the initial design intent, which is based on the experience and intuition of the designer. The traditional design procedure is an iterative process. It starts with an initial concept design that is based on the experience, knowledge and intuition of the designer. Analysis and redesign steps are carried out to evaluate and modify the product layout. This is a time-consuming and inefficient procedure that can create sub-optimal structure layouts because the starting topology is not optimal. Topology optimisation has been proven very effective in determining the topology of the initial design structure for component development in the conceptual design phase. The aim of design optimisation is to find the best possible or optimal structure layout for a product without sacrificing functionality and manufacturability conditions. The flowchart of the proposed approach is shown in Fig. 3.

The present approach includes eight steps; in the first step, the current state of the die design and sheet metal stamping process in literature is searched to identify recent developments and shortcomings of the present procedures regarding future research directions. At the next step, the physical tests to evaluate the simulation results are defined regarding the measurement of displacement and the stress and strain values on die surface. A sample die for which the results could

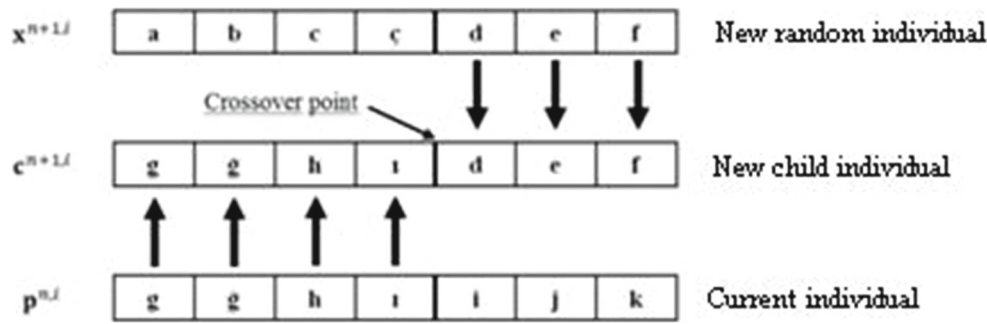


Fig. 2 The crossover operation of DEBVs

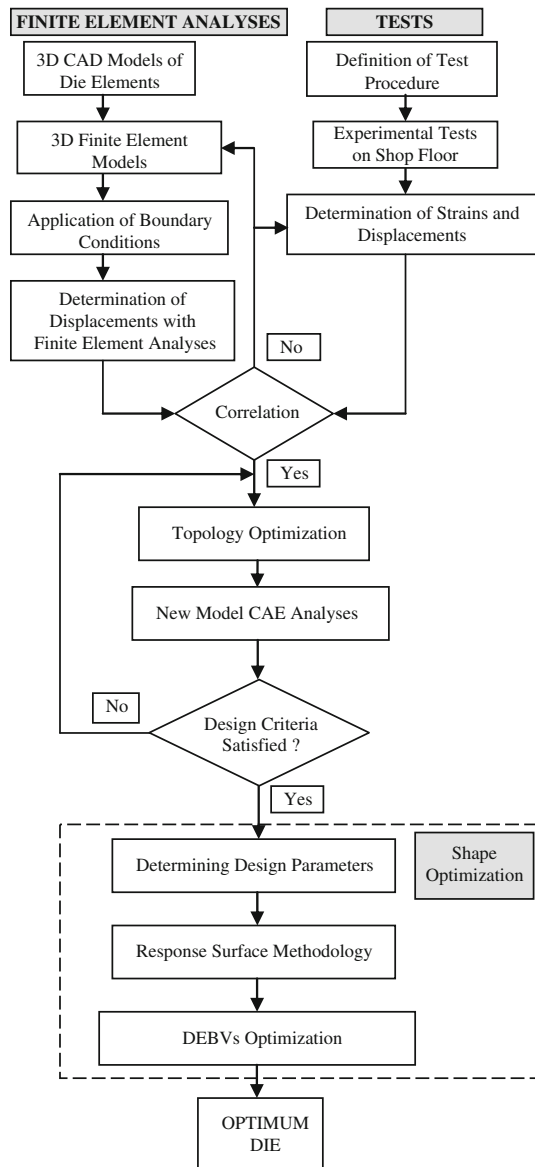


Fig. 3 The flowchart of the present approach

be immediately applied to the production line is chosen to employ the proposed approach. After that, maximum pressure values on the die surfaces and restrictions due to die

fastening systems are examined. Before the finite element analyses, bad surfaces on the solid model are corrected. In order to find the optimal mesh distribution, various mesh techniques are tested, and a mesh convergence process is carried out. At verification step, the results of simulations and tests are compared to verify the finite element model. In topology optimization step, various die designs based on desired objectives and constraints are generated using the topology optimisation approach. Finally, alternative optimal structures acquired from the previous step are evaluated to define the outlines of the best die structure in terms of manufacturability and applicability issues (Fig. 3).

The computer aided design (CAD) geometry of the die and the press table have very complex and small surfaces (Fig. 4a, b), so transformation of the model to the analysis software (ABAQUS) was done very carefully for the pre-processing of the finite element (FE) analysis (Simulia 2008). Redundant geometric objects causing defective mesh are debugged and prepared for meshing. As the boundary conditions of the bottom surfaces of the press table are fixed, forces are applied to the contact surfaces on the die matrix at two stages. In the first stage, a blank holder force is applied on the surfaces shown in Fig. 4c. In the second stage, a punch force is applied on the surfaces shown in Fig. 4d.

Finite element simulation of the die process was performed using 3D simulation models, including models of the die matrix, drawbead and press table. The effect of a blank holder was also taken into account. The maximum displacement values of the die components were calculated using finite element codes. The calculation time can be different for each analysis because of factors such as simulation definitions, the solver used and the hardware properties. In this study, it can be seen that the pre-processing stage and the solver properties have had a very important role in the process performance of FE simulations of die components. Experimental shop floor tests were performed for the purpose of obtaining the necessary acceleration and displacement data for the die model. As a first step, the sensor location points were investigated. Therefore, the maximum stress and the displacement contours of the dies were observed using finite

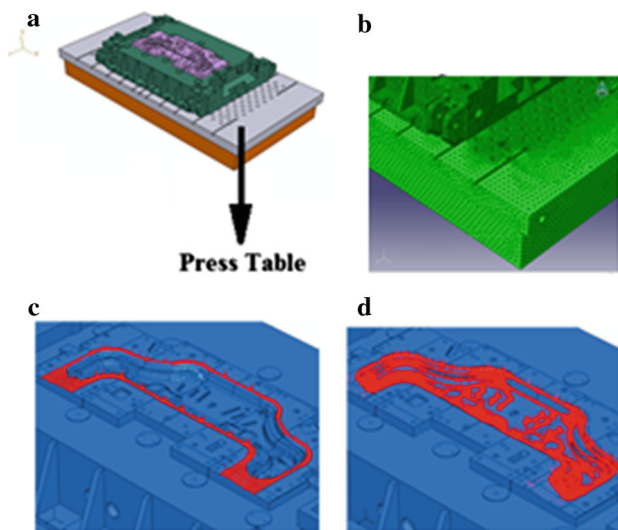


Fig. 4 a The CAD geometries of dies with press table, b mesh structure, c blank holder force surfaces and, d punch force surfaces

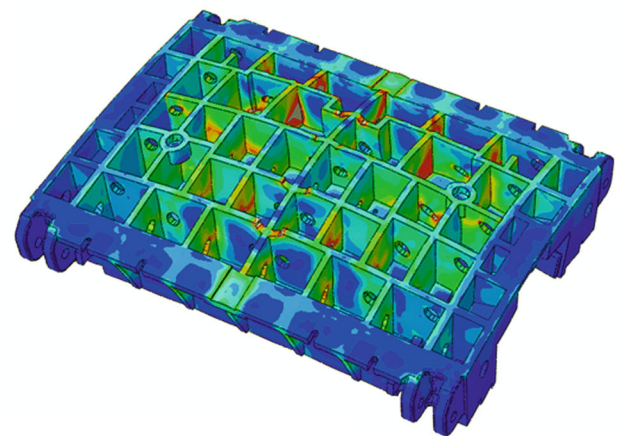
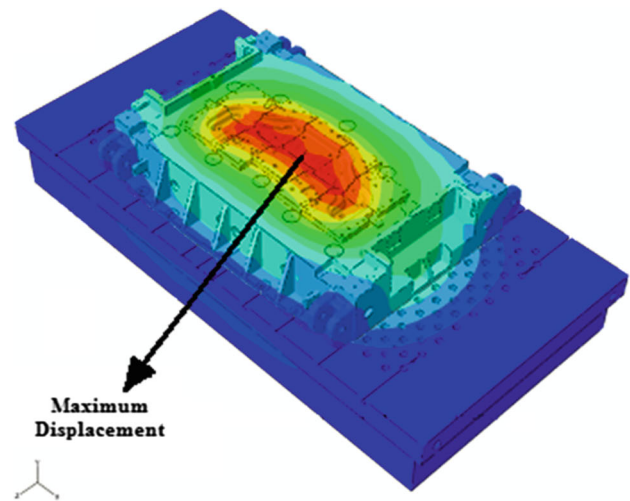


Fig. 6 Simulation results with maximum displacement and stress

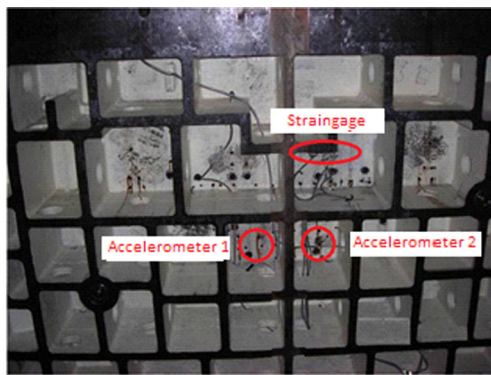


Fig. 5 Accelerometer locations on the die and the signal collector with 16 channels

element codes. This process helped in the process of locating the accelerometers and strain gauges. A signal collector with 16 channels was used for collecting accelerator and strain values on certain points of the die. The experimental test results were collected for further comparisons against simulation results. Then, the measured numerical data from certain points were transformed to obtain the displacement and stress values (Fig. 5).

Experimental tests were performed to verify the present approach and the model definitions against FE analysis results (Fig. 6). A very good correlation for the present study was obtained for this case. The difference between the maximum displacement value calculated from the simulation and the test was approximately 1 %.

Evaluation of DEBVs with the engineering optimization test problems

The most practical way to show the accuracy of a new developed algorithm is solving the test functions and engineering optimization problems which were solved earlier by other algorithms. Generally finding the best results using the new developed algorithm is expected. In this study when choosing the engineering optimization problem to show the DEBVs's efficiency, two important points were taken care of; (1) engineering optimization problem was not chosen randomly and (2) enough information (singularity, modality,

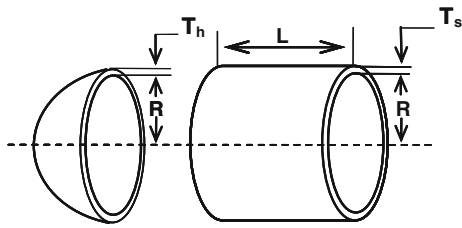


Fig. 7 Design variables of pressure vessel engineering design optimization problem (Kannan and Kramer 1994)

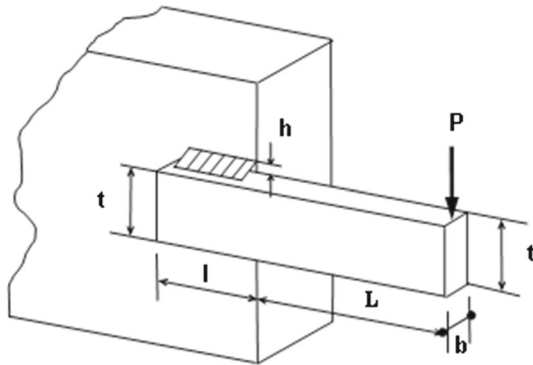


Fig. 8 Design variables of welded beam design optimization problem (Rao 2009)

noise, dimensionality, differentiability, etc.) about engineering optimization problem was obtained. In addition to all these, the selected test problem was solved 30 times for efficiency and robustness. Also the same population numbers, crossover rates and differential scale factors were used in the problem.

To strengthen the perfect performance of DEBVs, the pressure vessel engineering design optimization problem and welded beam design optimization problem which were solved by other algorithms to show their performance were handled (Figs. 7, 8).

A cylindrical pressure vessel is capped at both ends by hemispherical heads as shown in Fig. 7. The total cost including the cost of material, cost of forming and welding, is to be minimized (Kannan and Kramer 1994). The design variables are; the thicknesses of the shell (T_s), the head of the shell (T_h), the inner radius (R), the length of the cylindrical section (L). The variables R and L are continuous while T_s and T_h are integer multiples of 0.0625 inch which are the available thicknesses of rolled steel plates (Fig. 7).

In the mathematical model of pressure vessel, T_s , T_h , R and L parameters are represented by x_1 , x_2 , x_3 and x_4 , respectively. The objective function is to minimize the total cost including the cost of material, cost of forming and welding:

Objective Function (Minimization) (Kannan and Kramer 1994):

$$f(x) = 0.6224x_1x_3x_4 + 1.7781x_2x_3^2 + 3.1661x_1^2x_4 + 19.84x_1^2x_3 \tag{4}$$

Constraint Functions (Kannan and Kramer 1994):

$$\begin{aligned} g_1(x) &= -x_1 + 0.0193x_3 \leq 0 \\ g_2(x) &= -x_2 + 0.00954x_3 \leq 0 \\ g_3(x) &= -\pi x_3^2x_4 - \frac{4}{3}\pi x_3^3 + 1296000 \leq 0 \\ g_4(x) &= x_4 - 240 \leq 0 \end{aligned} \tag{5}$$

Boundary Constraints (Kannan and Kramer 1994):

$$\begin{aligned} 0.0625 &\leq x_1 \leq 99 \text{ (integer multiples of 0.0625)} \\ 0.0625 &\leq x_2 \leq 99 \text{ (integer multiples of 0.0625)} \\ 10 &\leq x_3 \leq 200 \\ 10 &\leq x_4 \leq 200 \end{aligned} \tag{6}$$

This pressure vessel problem has been solved by Deb (1997) using a simple genetic algorithm with binary representation, and a genetic adaptation search algorithm (Table 1).

It has also been solved by Kannan and Kramer (1994) using an augmented Lagrange multiplier based method. Sandgren (1988) has also solved this problem using a branch and bound technique. The first constraint of the problem is not satisfied when using the Kannan and Kramer (1994) method. Similarly the third constraint of the problem is not satisfied when using the Sandgren’s (1988) branch and bound technique. Coello and Montes (2002) has solved the problem using dominance-based tournament selection mechanism with 30 runs and they have handled the best results with 80,000 function evaluations so as to satisfy all constraints. All results were compared against those produced by the approach DEBVs proposed in this paper, and are shown in Table 1. The solutions shown in the Table 1 are the best solutions produced after 30 runs. When the problem was solved by differential evolution (DE) algorithm, a good result (6059.719052) was handled with 5,000 function evaluations compared to other methods. When the problem was solved by DEBVs proposed in this paper, the best result (6059.714337) was handled with 5,000 function evaluations and with 0.000035 standard deviation thereby satisfying all constraints.

Welded beam design optimization problem was first handled by Ragsdell and Phillips (1976) and Rao (2009) was redesigned it for minimum cost subject to constraints on shear stress in weld (τ), bending stress in the beam (σ), buckling load on the bar (P_c), end deflection of the beam (δ), and side constraints. The mathematical model of this problem is as follows;

Objective Function (Minimization) (Ragsdell and Phillips 1976):

$$f(x) = 1.10471x_1^2x_2 + 0.04811x_3x_4(14.0 + x_2) \tag{7}$$

Table 1 The best results for the pressure vessel engineering design optimization problem

The best results	$x_1(T_s)$	$x_2(T_h)$	$x_3(R)$	$x_4(L)$	$f(x)$
Sandgren (1988)	1.125000	0.625000	47.700000	117.701000	8,129.103600
Kannan and Kramer (1994)	1.125000	0.625000	58.291000	43.690000	7,198.042800
Deb (1997)	0.937500	0.500000	48.329000	112.679000	6,410.381000
Coello (2000)	0.812500	0.437500	40.323900	200.000000	6,288.744500
Coello and Montes (2002)	0.812500	0.437500	42.097398	176.654047	6,059.946341
Karen (2005), Karen et al. (2008)	0.812500	0.437500	42.098436	176.637341	6,059.730000
DE	0.812500	0.437500	42.098422	176.636968	6,059.719052
DEBVs	0.812500	0.437500	42.098446	176.636596	6,059.714337

Bold value indicates the new best result

Table 2 The best results for the welded beam engineering design optimization problem

The best results	$x_1(h)$	$x_2(l)$	$x_3(t)$	$x_4(b)$	$f(x)$
Deb (1991)	0.248900	6.173000	8.178900	0.253300	2.433116
Ragsdell and Phillips (1976)	0.245500	6.196000	8.273000	0.245500	2.385937
Siddall (1972)	0.244400	6.218900	8.291500	0.244400	2.381543
Rao (2009)	0.244400	6.217700	8.291500	0.244400	2.381000
Ray et al. (2002)	0.167880	4.645894	8.928757	0.219162	1.900000
Coello (1999)	0.208800	3.420500	8.997500	0.210000	1.748309
DE	0.2015340	3.558397	9.056079	0.206152	1.736723
Coello and Montes (2002)	0.205986	3.471328	9.020224	0.206480	1.728220
DEBVs	0.205730	3.470489	9.036624	0.205730	1.724852

Bold value indicates the new best result

Constraint Functions (Ragsdell and Phillips 1976):

$$\begin{aligned}
 g_1(x) &= \tau(x) - \tau_{\max} \leq 0 \\
 g_2(x) &= \sigma(x) - \sigma_{\max} \leq 0 \\
 g_3(x) &= x_1 - x_4 \leq 0 \\
 g_4(x) &= 0.10471x_1^2 + 0.04811x_3x_4(14.0 + x_2) - 5.0 \leq 0 \\
 g_5(x) &= 0.125 - x_1 \leq 0 \\
 g_6(x) &= \delta(x) - \delta_{\max} \leq 0 \\
 g_7(x) &= P - P_c(\mathbf{x}) \leq 0
 \end{aligned} \tag{8}$$

where the stress values are defined by Yokota et al. (1999) as follows (Ragsdell and Phillips 1976);

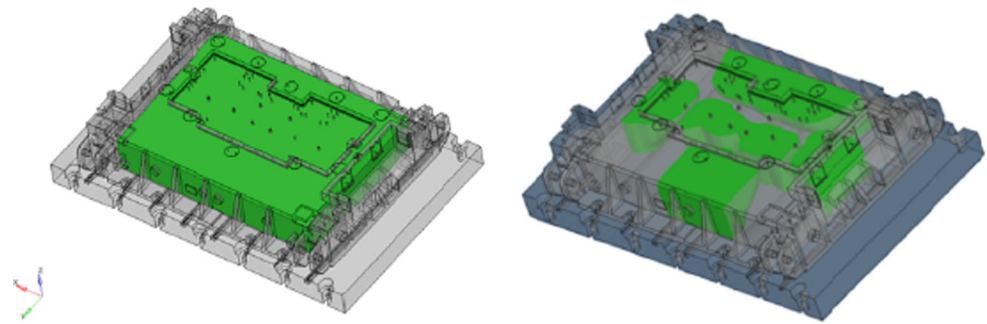
$$\begin{aligned}
 \tau(x) &= \sqrt{(\tau')^2 + 2\tau'\tau''\frac{x_2}{2R} + (\tau'')^2} \\
 \tau' &= \frac{P}{\sqrt{2}x_1x_2} \\
 \tau'' &= \frac{MR}{J} \\
 R &= \sqrt{\frac{x_2^2}{4} + \left(\frac{x_1 + x_3}{2}\right)^2} \\
 P &= 6000 \text{ lb} \\
 M &= P \left(L + \frac{x_2}{2}\right)
 \end{aligned}$$

$$\begin{aligned}
 J &= 2 \left\{ \sqrt{2}x_1x_2 \left[\frac{x_2^2}{12} + \left(\frac{x_1 + x_3}{2}\right)^2 \right] \right\} \\
 L &= 14 \text{ in} \\
 \tau_{\max} &= 13600 \text{ psi} \\
 \sigma(x) &= \frac{6PL}{x_4x_3^2} \\
 \sigma_{\max} &= 30000 \text{ psi} \\
 \delta(x) &= \frac{4PL^3}{Ex_3^3x_4} \\
 E &= 30000000 \text{ psi} \\
 \delta_{\max} &= 0.25 \text{ in} \\
 P_c(x) &= \frac{4.013E\sqrt{\frac{x_3^2x_4^6}{36}}}{L^2} \left(1 - \frac{x_3}{2L}\sqrt{\frac{E}{4G}} \right) \\
 G &= 12000000 \text{ psi}
 \end{aligned} \tag{9}$$

When the problem was solved by DEBVs proposed in this paper, the best result (**1.724852**) was handled with **0.000035** standard deviation thereby satisfying all constraints (Table 2).

These two constraint test problems which were frequently used as a test tool for many new algorithms were solved with the developed DEBVs algorithm and better results with less function evaluation numbers were handled when comparing the results of other algorithms. So developed DEBVs

Fig. 9 Design space (green volume) and material distribution after topology optimization (Color figure online)



algorithm can be used confidently in the die design optimization problem.

Solving die design optimization problem with DEBVs

In this study, topology optimisation for a die design of a vehicle panel part was performed in accordance with the determination of target parameters (minimum volume and maximum stiffness). During the topology optimisation, the shape and size of the structure can be changed, but the topology of the structure is not changed. Therefore, optimisation techniques have to be considered in the conceptual design phase to create an optimal initial design layout. In the conventional process, the designer may consider many alternative topologies, and one of them is chosen as the final component layout. It is a trial-and-error approach and highly depends on the designer's experience, creativity and heuristics. This procedure may result in a final component layout that is non-optimal. However, in the topology optimisation approach, the designer does not have to choose the optimal topology among alternatives, and no prior knowledge about the topology is required.

The design space must be defined for the part while taking into account the functionality. For this reason, a definition of the design space as the region in the inner side of the die (green part of the model) is applied, as shown in Fig. 9. The optimal material distribution has been acquired using a topology solver for the design space. The objective of topology optimisation is to determine the material distribution for the desired stiffness and desired volume. For the topology optimisation model, the objective function and the constraints are defined, and the compliance is selected as the objective function with decreasing volume as a constraint (Altair Engineering Inc 2008). It can be seen that material has accumulated in the middle and along the sides of the part. There is no material at the corners of the part, as shown in Fig. 9.

After topology optimization different die structures are generated based on topology design approach considering the manufacturability and cost factors (Fig. 10).

Third alternative (A3) is preferred for shape optimization among four alternative die structures (Fig. 10). About 14 %

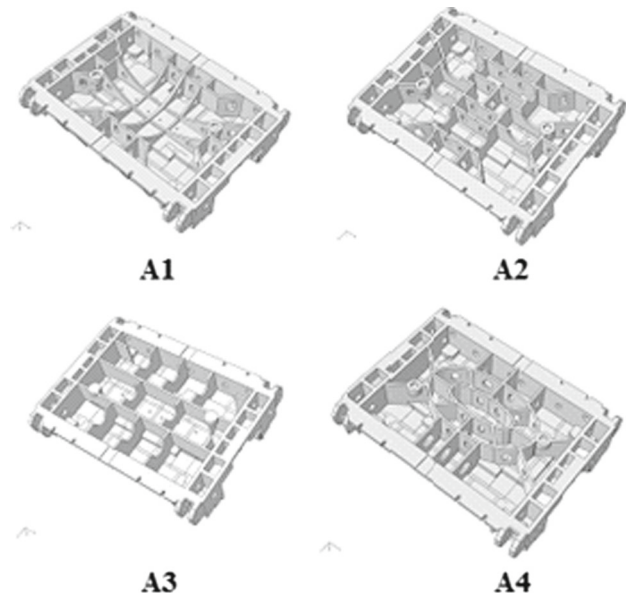


Fig. 10 Alternative die models after topology design approach

mass decrease is obtained for this model. At the shape optimization stage of the selected die design, the A3 model was taken into account to define shape parameters. The first step for the optimization formulation of the current die model is the selection of an objective function that represents the purpose of the design exactly. The design objective of the shape optimization is minimizing the mass. The design variables of selected model are; the thickness (t) and height (h) of die stiffener structure (Fig. 11).

In shape optimization process only one analysis takes about one hour as well, so computational time of overall optimization process will be very long. Thus design of experiment (DOE) is employed to decrease the computational time (Karen 2011). DOE method is used for preparation of the optimization process with certain parameters. Design parameters of sample die structure change at the range of $10 < t < 100$ and $100 < h < 500$ mm. It is decided to do 50 experiments for well-defining the design space. Three analysis of variance plans (ANOVA) are created for volume, stress and maximum displacement.

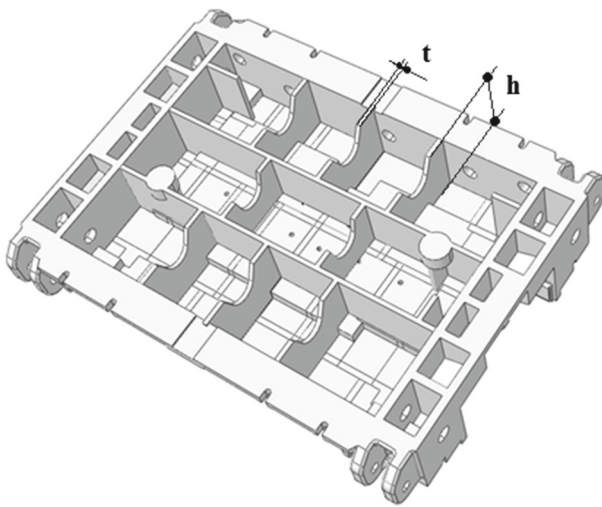


Fig. 11 Parameters of A3 die design model for shape optimization

During the optimisation process intermediate values of experiments are needed and to acquire the values of intermediate values in the experiments, functions must be created to denote volume, stress and maximum displacement (Kaya et al. 2010). Response surface methodology (RSM) introduced by Box and Wilson (1951) investigates the relationships between input variables and one or more output variables. In this method, polynomials are fitted to the data created using design of experiments as follows;

Fourth-degree approximation (quartic) for *volume* (Karen 2011):

$$f_v(h, t) = 110611572.48 + (5090491.53h + 679040.56t) + (-26802.61h^2 - 24155.66t^2 + 11231.04ht) + (67.49h^3 + 324.58t^3 - 0.10552h^2t - 63.79475ht^2) + (-0.05560h^4 - 1.47364t^4 + 0.00118h^3t + 0.31135ht^3 - 0.00906h^2t^2) \tag{10}$$

Fourth-degree approximation (quartic) for *stress* (Karen 2011):

$$f_s(h, t) = 163.72 + (-0.19361h - 5.92460t) + (0.00064h^2 + 0.12783t^2 - 0.00160ht) - 0.000002h^3 - 0.00136t^3 + 0.000004h^2t + 0.00005ht^2 + (0.000000002h^4 + 0.000005t^4 - 0.000000004h^3t - 0.0000003ht^3 - 0.0000001h^2t^2) \tag{11}$$

Fourth-degree approximation (quartic) for *maximum displacement* (Karen 2011):

$$f_{md}(h, t) = 0.77062 + (0.00013h - 0.01888t) + (0.000002h^2 + 0.00055t^2 - 0.00004ht) + (-0.000000002h^3 - 0.000007t^3 + 0.000000002h^2t + 0.0000006ht^2) - (0.000000000004h^4 + 0.00000003t^4 + 0.00000000001h^3t - 0.000000003ht^3 - 0.00000000007h^2t^2) \tag{12}$$

The coefficient of determination, R^2 values for each of those 3 approximation response functions are 0.999991, 0.993063 and 0.995027, respectively. Thus, three quartic fourth-degree approximation response functions for volume, stress and maximum displacement. Eqs. (10), (11) and (12) were employed for the optimisation process.

In the optimisation process, the objective is to minimise the volume, in other words, to find the optimal values of h and t that minimize the volume formulated in Eq. 10. The DE and DEBVs algorithms are used to search the optimal design parameters. Two constraints, such as stress (Eq. 11) and maximum displacement (Eq. 12), must be less than 50 and 0.33, respectively.

The optimisation problem is solved by DE and DEBVs with the number of populations set to 10 and with the number of generations set to 25. For both algorithms the function evaluation number is 250 and for the robustness the die design optimization problem was solved with 30 runs using differential scale factor as 0.85 and crossover rate as 0.9. The best results were obtained with DEBVs. The optimal values of h and t were computed as $h = 259.6546$ and $t = 93.7187$ mm. Significant results were obtained that reduced the mass by

Table 3 The results of die design optimization problem using DE and DEBVs

	Mass variation (% *)	Maximum stress variation (%)	Maximum displacement variation (%)	Total run time (%)
Current model	100	100	100	–
Topology optimization	83	96	149	–
Shape optimization using DE (Karen et al. 2012)	76.43	28	109	100
Shape optimization using DEBVs	76.39	28	109	65

Bold Value indicates the new best result
 * % Variation = Mass of current model – Mass after optimization processes

approximately 24 % and that decreased the current stress by approximately 72 %. After the optimisation process, the maximum displacement decreased from 149 % to a negligible value of 109 % (Table 3). These data are calculated by using a simple proportion formulation. The most important point is that the total run time is reduced about 35 % using DEBVs in comparison with DE (Karen et al. 2012) shown in Table 3.

Conclusions

This paper has introduced a new intelligent die design based on shape and topology optimization using improved differential evolution and response surface methodology. The new approach is based on a methodology that uses the best vectors in the population as differential vectors (DEBVs) in mutation strategy. The proposed approach performed well in the engineering optimization problem both in terms of the number of objective function evaluations required and in terms of the quality of the solutions found. The results produced were compared against those generated with other evolutionary and mathematical programming techniques reported in the literature. Using DEBVs algorithm the best results were handled.

This improved intelligent methodology was used in the design stage of die, and significant results were obtained: the mass was reduced approximately 24 %, the current maximum stress decreased approximately 72 %, and the maximum displacement decreased from 149 % to a negligible value of 109 %. The most important point is that the total run time is reduced about 35 % using DEBVs in comparison with DE.

Using this methodology in the design stage of die and sheet metal stamping, major improvements to the vehicle development process can be made, such as reducing the weight and the cost of die, reducing the labour costs during pattern practice and reducing the environmental damage or CO₂ emissions by reducing the amount of cast iron.

The results showed that the present simulation-based topology design approach integrated with response surface methodology and differential evolution can be used to support the designer in designing optimal die models according to desired objectives and constraints. It is also seen that the present approach can support the designer in creating innovative die design structures.

As part of our future work, we plan to analyse the crossover mechanism and additionally, we are considering the extension of other multi-objective optimization techniques to handle constraints in evolutionary algorithms. Further this developed method can be implemented to the other kinds of dies such as bending, cutting, etc. And also overall press models can be taken into account for calculating the deflections in order to increase the correlation.

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