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Multi-Objective Tabu Search Algorithm to Minimize Weight and Improve Formability of Al3105-St14 Bi-Layer Sheet

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ABSTRACT

Nowadays, with extending applications of bi-layer metallic sheets in different industrial sectors, accurate specification of each layer is very prominent to achieve desired properties. In order to predict behavior of sheets under different forming modes and determining rupture limit and necking, the concept of Forming Limit Diagram (FLD) is used. Optimization problem with objective functions and important parameters aims to find optimal thickness for each of Al3105-St14 bi-layer metallic sheet contributors. Optimized point is achieved where formability of the sheet approaches to maximum extent and its weight to minimum extent. In this paper, multi-objective Tabu search algorithm is employed to optimize the considered problem. Finally, derived Pareto front using Tabu search algorithm is presented and results are compared with the solutions obtained from genetic algorithm. Comparison revealed that Tabu search algorithm provides better results than genetic algorithm in terms of Mean Ideal Distance, Spacing, non-uniformity of Pareto front and CPU time.

Keywords: Bi-layer metallic sheet; Forming limit diagram (FLD); Pareto front; Tabu search algorithm.

1 INTRODUCTION

APPLICATION of bi-layer metallic sheets in different aeronautical, oil, gas and petrochemical, defense and automobile industries is expanding. Generally, combining two layers, each with a brilliant property will lead to provide a sheet with better properties in comparison with each of its contributors. Weight and formability of bi-layer metallic sheets rely on each layer's material and thickness. To measure weight, density is used and to measure formability and estimation of rupture and necking, FLD curves are applied. FLD concept for the first time was presented by Keeler and Backhofen [1] and later by Goodwin [2]. Semiatin and Piehler [3], [4] investigated steel bi-layer sheet

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with aluminum cladding, and aluminum bi-layer sheet with steel cladding under tensile loads in axial and non-axial directions. Furthermore, analysis of formability of Al3105-St14 was investigated by Darabi et al. [5]. They used the Hill and Barlat-Lian yield criteria to determine the FLD of bi-layer sheet and showed their approaching associated with Barlat-Lian yield criteria was compatible with experimental results. Deilami Azodi et al. [6] also investigated the ductile fracture criteria to estimate the FLD of Al3105-St14 bi-layer sheet and showed that results of Oh and Brozzo ductile fracture criteria were more compatible with experiments. Tabu search algorithm, using different memory structures, considers different situations to free or limit search process that avoids converging to local optimized points and leads to global optimum. One of influential parameters on applicability and accuracy of Tabu search algorithm is memory structure in neighborhood and Tabu list. With a decrease in neighborhood, algorithm's accuracy increases though it is probable that all possible answers in the domain are not considered. Moreover, increasing in Tabu list, decreases the probability of entering into loops. However, recording and analyzing all possible entities in this list is dramatically time consuming. Genetic algorithm is based on evolution of species in the nature and is one of the search algorithms with natural selection and genetics. During evolution, generations are developed and thrived and those who better adapt themselves with their environment, have more chance to regenerate while others gradually become extinct. Therefore, species increasingly match themselves with next generations [7]. Heuristic algorithms from the beginning of advent of the operations research methods have been used to solve combinatorial problems. With development of complexity theory, it was argued that probability of finding an effective procedure to achieve exact accurate solutions in NP-hard problems is very low. Although many procedures have been introduced and tested, the most applicable concept is based on local search techniques [8]. The most limiting property of local search algorithm is finding local optimized points as the best point. To address this issue, Tabu search algorithm with real usage of memory structure was introduced [9]. The origin of this metaheuristic algorithm is when it was used in nonlinear generalized set covering problems [10]. Tabu search algorithm for the first time was introduced by Glover [11] to avoid the repetition of useless paths in search for optimized points and was initiated as a strategy to solve combinatorial problems. Later the parametric form of Tabu search algorithm using move according to branch and bound method was developed [12]. Parametric form of this algorithm, using its search memory structure that is more flexible, has modified parametric branch and bound method. Jaeggi et al. developed a multi-objective Tabu search algorithm for continuous optimization problems [13]. Genetic algorithm with engineering applications is first introduced by Holland [14] based on biology. First optimization problem, using multi-objective genetic algorithm was reported by Schaffer [15]. Later, other forms of genetic algorithm like evolutionary strategy with Pareto archive [16], evolutionary multi-objective optimization with selection based on region [17], multi-objective evolutionary algorithm [18] and dynamic multi-objective evolutionary algorithm [19] were introduced.

In this paper, using assumptions and modeling results of the study by Darabi et al. [20], a combination of St14 sheet with its excellent mechanical properties and Al3105 sheet with its low weight as a bi-layer metallic sheet is considered. The concept of FLD is utilized to predict behavior of sheets under different forming modes with rupture limit and necking. In addition in this paper, multi-objective Tabu search algorithm is used to optimize the considered problem and find optimal thickness for each of Al3105-St14 bi-layer metallic sheet contributors. By changing each layer's thickness, using FLD and Tabu search algorithm, optimized results with the aim of maximum formability and minimum weight of bi-layer sheet are computed. Finally, results from Tabu search algorithm are compared with those of genetic algorithm.

2 THEORETICAL APPROACH

2.1 Optimization

Optimization is an approach towards the best state among possible solutions that involves selection among many responses. Since there are constraints in real problems, just a better response is selected instead of the best one. The relative suitability of each point is described by one or more objective functions and constraints over independent variables -called design variables- are considered. In real world problems, objectives are more than one and mostly opposite. This is called a multi-objective optimization problem. In such a problem, there is not just one optimum but a set of optimized points with different trade-offs called Pareto optimized points [21].

General form of a multi-objective optimization problem is presented according to Eq. (1):

$$\begin{aligned} &Optimize \quad f(x)=\{f_1(x),...,f_k(x)\} \quad k\geq 2 \\ &s.t. \quad h_j(x)=h_j(x_1,...,x_n)\leq 0 \quad 1\leq j\leq m \end{aligned} \tag{1}$$

where $f(x)$ is a set of objective functions and all $h_j(x)$ are constraints.

Eq. (2) presents problem vector where x is parameter vector and x_i is the value of i^{th} parameter.

$$x = (x_1,...,x_n) \tag{2}$$

Response domain of an optimization problem is a set of all possible solutions satisfying all constraints and the optimum response is the point in which objective functions yield the best-desired answer. During searching for an optimized answer, the concept of domination emerges which is the basis for Pareto front. In searching for a minimum, response vector x_1 extremely dominates x_2 when Eq. (3) is right.

$$f_i(x_1) \prec f_i(x_2) \quad \forall i = 1,...,k \tag{3}$$

Response vector x_1 fairly dominates x_2 when Eq. (4) is right

$$\begin{aligned} &f_i(x_1) \le f_i(x_2) \quad \forall i = 1,...,k \\ &f_i(x_1) \prec f_i(x_2) \ \text{ for at least one } \ i = 1,...,k \end{aligned} \tag{4}$$

Pareto front is a set of dominant responses in the domain of possible points where its corresponding variables cannot be improved simultaneously. In other word, improving one function in Pareto front leads to change the other adversely [22].

2.1.1 Optimization using Tabu search algorithm

Tabu search algorithm is based on neighborhood search and human memory is modeled within it. Human memory records its observations using effective but simple structure of data. To achieve an optimized point, Tabu search algorithm starts with a random response in the response domain and its corresponding objective functions values are recorded. Then using predetermined parameters, neighborhood set is produced and analyzed and the best point is ascertained. Then, Tabu list is known in the way that previous response, until specific number of iteration, is included in this list and algorithm avoids -except in some cases- using these points. Within each loop, algorithm produces neighborhood set and its best answer is selected. If there is no better point in the neighbor set, algorithm checks aspiration criterion. According to this criterion, if neighborhood response is better than already-known-best response, even though it belongs to Tabu list, algorithm introduces this point as the answer. After transferring to neighborhood response, Tabu list is updated. It means that previous step which led to present response is included to Tabu list to avoid converging again to it and consequently it avoids local optimization. In this step, based on the size of the Tabu list, some of the previous responses are discarded according to first-in-first-out (FIFO) method. These steps are repeated until finishing condition that is specified based on desired accuracy, time and nature of the problem is satisfied.

2.1.2 Optimization using genetic algorithm

In genetic algorithm, a generation of points are constantly produced and modified. Each response is assigned with a set of characters. In each iteration, genetic algorithm works on a set of generations and applies random variations on it using ideal models of genetic processes. In regeneration step, all strings are decoded and objective function value is computed for each point. Then, based on the evaluation score of each point that shows the possibility of being selected for the next generation, they are scored. Some strings are selected and new strings are produced by applying genetic functions and replaced with those in the previous generation so that the population of generation in different iteration stays constant. Random nature in selecting and discarding population relies on probability function of score. Population with higher score has a higher chance for combination and producing offspring for new generations and they also show higher resistance against being replaced. Therefore, in a competence based on objective function, population evolved with generations and the mean of objective function value increase with generation. Thus, the best populations of the current generation with high probability would be transferred to the next generation.

3 COMPUTATIONAL RESULTS

3.1 Modeling

In this problem, optimum combination of Al3105 and St14 is sought in the way that maximum formability of the bi-layer metallic sheet as well as minimum weight is achieved. A constraint on total thickness exists. Considering material properties and their formability and density, objective functions are derived and by using Tabu search and genetic algorithms, optimum values for objective functions are specified taking into account constraint.

3.2 Variables definition

Due to huge differences in density and formability of two Al3105 and St14 layers, selecting each layer's thickness plays a remarkable role in formability and weight of the bi-layer sheet. Therefore, variables of the problem are thickness of Al3105 and St14 layers. Eq. (5) and Eq. (6) specify ranges and constraints over the variables [20].

$$0mm \le t_{St14} \,\&\, t_{Al3105} \le 2mm \tag{5}$$

$$t_{St14} + t_{Al3105} = 2mm \tag{6}$$

3.3 Objective functions

Since the aim of the optimization is to minimize weight and maximize formability, these two are considered as objective functions. According to previous study by Darabi et al. [20], different states of thicknesses using full factorial method and formability and weight functions are available. Table 1, lists different states as well as function values are reported.

Table 1
Different possible states for layer's thickness [20].

N	t_{St14}	t_{Al3105}	Obj $_f$	Obj $_w$
1	0.0	0.0	0.000000	0.000000
2	0.0	0.5	0.065000	0.001350
3	0.0	1.0	0.090370	0.002700
4	0.0	1.5	0.097000	0.004050
5	0.0	2.0	0.108200	0.005400
6	0.5	0.0	0.208700	0.003925
7	0.5	0.5	0.183700	0.005275
8	0.5	1.0	0.178500	0.006625
9	0.5	1.5	0.173500	0.007975
10	0.5	2.0	0.161700	0.009325
11	1.0	0.0	0.255000	0.007850
12	1.0	0.5	0.231500	0.009200
13	1.0	1.0	0.223000	0.010550
14	1.0	1.5	0.206100	0.011900
15	1.0	2.0	0.205400	0.013250
16	1.5	0.0	0.272800	0.011775
17	1.5	0.5	0.260000	0.013125
18	1.5	1.0	0.243100	0.014475
19	1.5	1.5	0.233200	0.015825
20	1.5	2.0	0.215200	0.017175
21	2.0	0.0	0.287800	0.015700
22	2.0	0.5	0.272800	0.017050
23	2.0	1.0	0.257800	0.018400
24	2.0	1.5	0.253000	0.019750
25	2.0	2.0	0.245400	0.021100

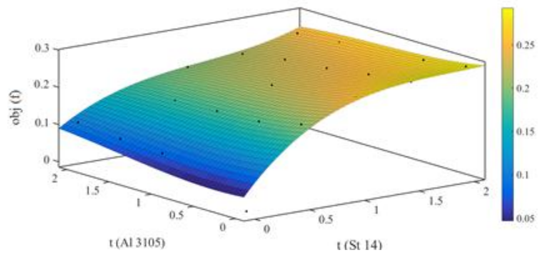

Fig.1
The best curved surface for bi-layer metallic sheet formability with different combinations of layer's thicknesses.

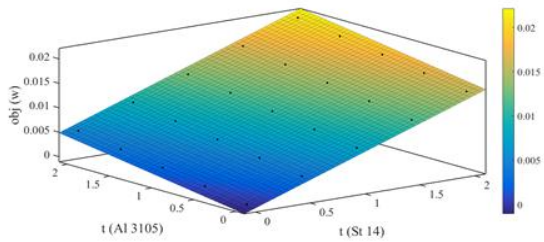

Fig.2
The best polynomial fit for weight (per m^2) function of bi-layer metallic sheet with different combinations of layer's thicknesses.

Using data in Table 1, the best-curved surface fitting data points is derived using MATLAB software based on mean square errors. Fig. 1 and Fig. 2 show the best fitted curves for formability and weight (per m^2) functions respectively [20].

Eq. (7) and Eq. (8) show formability and weight (per m^2) objective functions respectively [20].

$$\begin{aligned} Obj_f\,(t_{st14},t_{Al3105}) &= 0.0809+0.3127*t_{st14}-0.02075 \\ &*t_{Al3105}-0.1671*t_{st14}^{\;2}-0.06319*t_{st14}*t_{Al3105} \\ &+0.03242*t_{Al3105}^{\;2}+0.03105*t_{st14}^{\;3}+0.02559*t_{st14}^{\;2} \\ &*t_{Al3105}-0.002361*t_{st14}*t_{Al3105}^{\;2}-0.007827*t_{Al3105}^{\;3} \end{aligned} \tag{7}$$

$$Obj_w\,(t_{st14},t_{Al3105}) = 1.388e^{-18}+0.00785*t_{St14}+0.0027*t_{Al3105} \tag{8}$$

3.4 Results from Tabu search algorithm

Tabu search algorithm is used to find optimized points using a user-defined code in MATLAB software. Applied parameters of this algorithm are listed in Table 2.

Fig. 3 illustrates derived Pareto front for two objective functions. As can be observed, two objective functions are conflicting and there is no point where both objective functions are simultaneously maximized and minimized respectively.

Table 2
Applied parameters for Tabu search algorithm.

Parameter	Value
Population Size	*P*=50
Number of Neighborhood	*NN*=20
Tabu List Length	*TL*=30
Pareto Front Population Fraction	*Pp*=0.35
Termination Condition	*T*=600
Aspiration Criterion	In condition of last answer being better than other answers

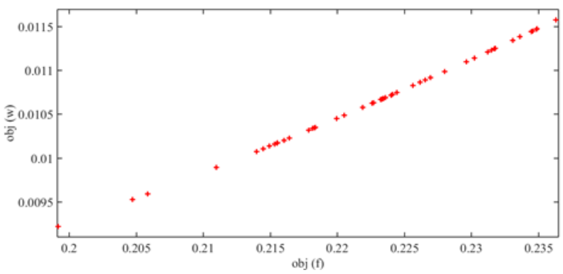

Fig.3
Pareto front for formability and weight objective functions derived with Tabu search algorithm.

3.5 Results from genetic algorithm

Genetic algorithm toolbox of MATLAB package is used and selected parameters are listed in Table 3. Since genetic algorithm toolbox, searches for minimum and objective functions in this study are conflicting, the formability objective function is mirrored given as an input to make both objective functions minimization problems. After finding out optimized responses, computed values for formability objective function are inversed.

Fig. 4 shows Pareto front for both objective functions using genetic algorithm.

Table 3
Applied parameters for genetic algorithm.

Parameter	Value
Population Size	P=50
Crossover Probability	Pc=0.80
Mutation Probability	Pm=0.35
Migration Fraction	Pg=0.20
Pareto Front Population Fraction	Pp=0.35
Termination Generation	T=600

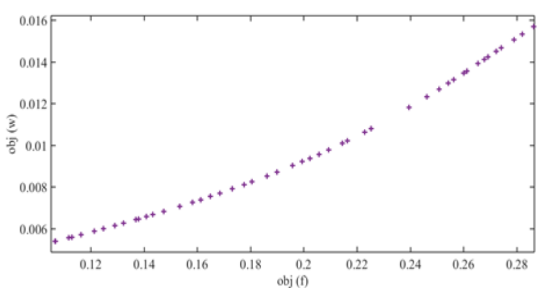

Fig.4
Pareto front for formability and weight objective functions based on genetic algorithm.

3.6 Comparison of Pareto fronts

In optimization problems with one objective function, the aim is to find the best response. While in multi-objective optimization problems, due to complication and confliction of objective functions, the aim is to find a set of optimized responses that are converging to ideal point and are varied. To evaluate the achievements in terms of quality, speed and accuracy, different metrics are presented [23]–[25]. Analysis of these metrics is presented in Table 4.

A metric to measure applicability of metaheuristic algorithms is comparing CPU time needed to achieve the results. The more time consuming is an algorithm, the less is its applicability and it considered non-feasible for general problems. Tabu search algorithm starts with only one response in comparison with genetic algorithm that uses a random population of responses and therefore, it is less time consuming. Furthermore, applying Tabu list to avoid repetitive computation of the already-known solutions leads to a decrease in CPU time. While in genetic algorithm, there is no procedure to stop repetitively computation of a solution.

Table 4
Metrics to compare Pareto fronts computed from Tabu search algorithm and genetic algorithm.

Metrics	Tabu search algorithm	Genetic algorithm
CPU time	158.19	175.72
Mean Ideal Distance (MID)	0.0136	0.0927
Spacing (S)	0.0346	0.1236
Maximum Spread (MS)	0.0371	0.1801
Non-uniformity of Pareto Front (NPF)	0.2264	0.4499

Mean Ideal Distance (MID) can be computed using Eq. (9). Higher value of MID proves higher applicability of the algorithm.

$$MID = \frac{\sum_{i=1}^{n}\sqrt{f_{1i} + f_{2i}}}{n} \tag{9}$$

where f_{1i} and f_{2i} are respectively the first and second objective function values for the i^{th} response of Pareto front and n is the number of responses of Pareto front.

Spacing shows the quality of distribution in Pareto response which is computed using Eq. (10). Lower spacing implies better distribution of the responses and consequently higher applicability of the algorithm.

$$S = \sqrt{\frac{1}{|n|}\sum_{i=1}^{|n|}(d_i - \bar{d})^2} \tag{10}$$

where d_i and d are computed using Eq. (11) and Eq. (12).

$$d_i = \min_{k \in n \cap k \neq 1} \sqrt{\sum_{m=1}^{2}(f_m^{\ i} - f_m^{\ k})} \tag{11}$$

$$\bar{d} = \sum_{i=1}^{n}\frac{d}{|n|} \tag{12}$$

where m is the number of objective functions.

Maximum spread can be computed using Eq. (13). Higher maximum spread which implicitly shows the diameter of the responses produced by Pareto front proves higher applicability of the algorithm because there are more selections to specify optimum point.

$$MS = \sqrt{\sum_{m=1}^{2}(\max_{i=1:|n|} f_m^i - \min_{i=1:|n|} f_m^i)^2} \tag{13}$$

Non-uniformity of Pareto front can be computed using Eq. (14). The lower *MS* is, the higher the accuracy of the algorithm is and therefore, responses are more reliable. This is due to the fact that wider fronts, generally, yields responses with higher uncertainties.

$$NPF = \sqrt{\frac{\sum_i(\frac{d_i}{d} - 1)^2}{|n| - 1}} \tag{14}$$

As can be seen from Table 4, Tabu search algorithm in terms of CPU time, Mean Ideal Distance, Spacing and non-uniformity of Pareto front yields better condition in comparison with genetic algorithm. While, genetic algorithm with wider search, provides varied optimum solutions.

3.7 Optimum point in Pareto front

In this paper, Minimum Distance Selection Method (MDSM) was used to find the most feasible point among Pareto front [26]. Based on this technique, first, Pareto front points are normalized and each objective function's value defines utopia point coordination. Here, due to conflicting nature of the objective functions achieving utopia point is not possible. The distances between each point on Pareto front and utopia point are computed and these are minimum for the knee point. Therefore, knee point can be presented as the best point in Pareto front.

Knee point computed based on Minimum Distance Selection Method (MDSM) as the optimum point in Pareto front is shown in Fig. 5 and Fig.6. Therefore, Al3105 and St14 optimum layer's thicknesses and values for objective functions -formability and weight (per m^2) - are according to Table 5.

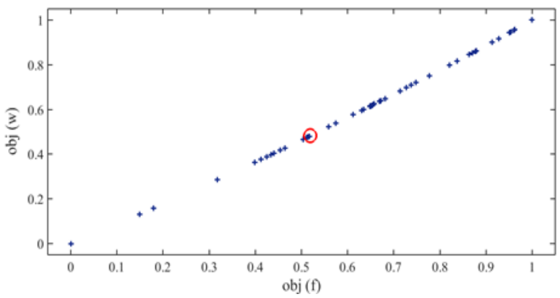

Fig.5
Knee point in normalized Pareto front for formability and weight objective functions as the best response based on Tabu search algorithm.

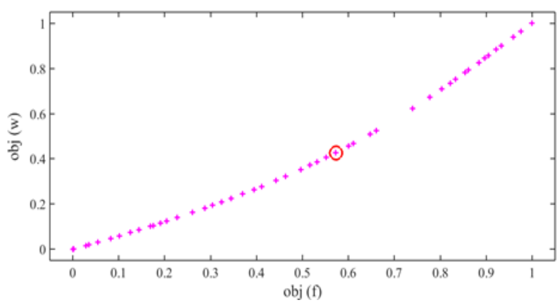

Fig.6
Knee point in normalized Pareto front for formability and weight objective functions as the best response based on genetic algorithm.

Table 5
Optimum thickness values for St14 and Al3105 layers and objective functions values for formability and weight at knee point for both Tabu search algorithm and genetic algorithm.

	Tabu search algorithm	Genetic algorithm
St14 Thickness	1.719	1.146
Al3105 Thickness	0.281	0.854
Formability value	0.21836	0.20930
Weight Value	0.01035	0.00979

4 CONCLUSION

In this paper, a combination of St14 sheet and Al3105 sheet with its low weight as a bi-layer metallic sheet was considered. Multi-objective Tabu search algorithm and FLD were used to find optimal thickness for each of Al3105-St14 bi-layer metallic sheet contributors with the aim of maximum formability and minimum weight. Searching the possible response space using Tabu search and Genetic algorithms and considering metrics to evaluate the applicability of metaheuristic algorithms showed that Tabu search algorithm outweighs genetic algorithm in terms of quality of solutions in discovering optimum layer's thickness to maximize formability and minimize weight of Al3105-St14 bi-layer metallic sheet. The wider range of Pareto response is the only metric in which genetic algorithm excels Tabu search algorithm. Moreover, the genetic algorithm presented several different near optimal and repetitive solutions at the same time that reduces the accuracy with the same iteration in comparison with Tabu search method. The application of other meta-heuristic algorithms such as particle swarm optimization (PSO) and simulated annealing (SA) may lead the problem to the better solutions and it can be a guideline for future studies.

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