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Multi-objective optimization of printing time and shape accuracy for FDM-fabricated ABS parts

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Abstract. Fused Deposition Modeling (FDM) is one of the most widely used Additive Manufacturing technologies that extrude a melted plastic filament through a heated nozzle in order to build final physical models layer-by-layer. In this research, a case study is presented in order to optimize process performance of a low cost FDM 3D printer. Taguchi method was first employed for the experimental procedure design and nine test parts were built according to L9 orthogonal array. The examined process parameters were the deposition angle, layer thickness, and infill ratio each one having three levels. Infill pattern was constant to honeycomb selection. Fabrication time of ABS (Acrylonitrile-Butadiene-Styrene) 3D printed specimens was measured during experiments and analyzed by using Analysis of Means (ANOM) and Analysis of Variance (ANOVA) techniques. Shape accuracy was measured by considering the parts' dimensions in X, Y and Z axes and expressed as the overall error for control. Regression models were developed to use them as objective functions for a group of multi-objective optimization algorithms. Multi-objective Greywolf (MOGWO), multi-objective antlion (MOALO), multi-verse (MOMVO) and multi-objective dragonfly (MODA) algorithms where implemented to simultaneously optimize the bi-objective FDM optimization problem. To evaluate the algorithms and judge superiority with reference to the non-dominated solution sets obtained the hypervolume (area) indicator was adopted. It was verified that algorithms perform differently to the problem formulated for optimizing the FDM process.

Keywords: Fused Deposition Modeling; Additive Manufacturing; ABS; printing time; shape accuracy; process optimization

1. Introduction

Globalization and keener competition among manufacturing industries has imposed the necessity to produce high-quality and low-cost products at the same time. Such volatile and competitive processing scenarios found in industry, have already drawn the interest of researchers to develop and deploy automation technologies in almost all branches of manufacturing engineering. To develop new products, it is mandatory to produce prototypes from solid models

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and examine their properties. This process is widely known as rapid prototyping (RP). RP utilizes operations where physical models are built by selectively adding material in the form of thin cross-sectional layers. Therefore, RP is also referred to as additive manufacturing. Currently, additive manufacturing technologies see services not only on communicating ideas and inspecting several design aspects but also on large-scale production of medical, biomedical and aeronautical models. The technologies available for additive manufacturing are fused deposition modelling (FDM); selective laser sintering (SLS); stereolithography (SL) laminated object manufacturing (LOM); solid ground curing (SGC) and 3D-printing. As it occurs to any other manufacturing process, the performance of additive manufacturing techniques is evaluated regarding surface roughness; dimensional accuracy and tolerances; production cost; mechanical properties; tribological properties, etc. Therefore, such objectives should be examined with reference to the effects of the independent process parameters. Additive manufacturing spans many objectives such as material strength of fabricated parts, dimensional accuracy and tolerance of geometrical features, wear properties under tribological tests, etc. The work presented in Sood *et al*. (2012a) studied the effect of five essential parameters on compressive strength of standard test specimens built through FDM. The study statistically examined the complex dependency of compressive strength by the independent variable controlling the FDM process and proposed a reliable regression equation to predict compressive strength. Similarly, the work presented in Sood *et al*. (2012b) examines the effect of independent FDM parameters on the sliding wear objective. The authors not only generated a reliable regression model to predict sliding wear, but they also optimized the response by having the model under the role of the objective function for a quantum-behaved particle swarm optimization (QPSO) algorithm for optimization. By examining the FDM parameters of line width compensation, extrusion velocity, filling velocity, and layer thickness, Peng *et al*. (2014) obtained experimental results referring to dimensional error, warp formation and built time for FDM-fabricated parts. Based on their experimental results they turned the triple-bounded problem to a single-objective one by formulating a single comprehensive response with fuzzy inference system. The relation between their single response and the independent variables was obtained by employing the 2nd order response surface methodology, the validity of which was further evaluated via a neural network. Their objective function was generated using the “penalty” function whilst it was solved with a commercially available genetic algorithm. Guralla and Regalla (2014), investigated the relationships between two quality objectives: tensile strength and volumetric shrinkage of FDM-fabricated standard specimens and the independent parameters of build interior, horizontal build direction and vertical build direction. By conducting the analysis of variance, an empirical model per objective was generated and served as the objective function for process optimization. The problem formulated was a multi-objective one and was solved by implementing the non-dominated sorting genetic algorithm, NSGA-II (Deb *et al*. 2002). Finally, NSGA-II obtained a Pareto front of non-dominated solutions that simultaneously satisfy the maximization requirement for tensile strength and minimization requirement for volumetric shrinkage. Another noticeable study concerning the multi-objective optimization of FDM-fabricated parts is the one presented in the work of Sood *et al*. (2010) where tensile, flexural and impact strengths are simultaneously maximized by adopting the “desirability function” concept. The three objectives were experimentally investigated by considering layer thickness, part orientation, raster angle, raster width and air gap as the independent process parameters under a central composite design. For these three objectives, empirical models relating objectives and corresponding independent parameters were generated and validated. Other noticeable contributions related to additive manufacturing optimization are those of Pandey *et al*. (2004),

Table 1 FDM Process parameters

Process Parameters	Level 1	Level 2	Level 3
Deposition angle (°)	0	15	30
Layer Thickness (mm)	0.09	0.19	0.29
Infill ratio (%)	10	20	30

Table 2 Taguchi orthogonal array L_9

a/a exp.	Deposition angle (°)	Layer thickness (mm)	Infill ratio (%)
1	0	0.09	10
2	0	0.19	20
3	0	0.29	30
4	15	0.09	20
5	15	0.19	30
6	15	0.29	10
7	30	0.09	30
8	30	0.19	10
9	30	0.29	20

Byun and Lee (2005), Thrimurthulu *et al*. (2004), Rong-Ji *et al*. (2009) and Canellidis *et al*. (2009) where genetic algorithms were applied to achieve optimal solutions for the objectives of the corresponding problems. Other more sophisticated algorithms have also been tested to optimize additive manufacturing. Tyagi *et al*. (2007) implemented a "stickers-based" intelligent algorithm inspired by DNA properties to achieve the optimal orientation during fabrication of models in laminated manufacturing process.

This work reports the optimization results obtained by implementing four modern algorithms namely Multi-objective Greywolf (MOGWO), multi-objective antlion (MOALO), multi-verse (MOMVO) and multi-objective dragonfly (MODA). The objective functions for algorithmic evaluation were the regression models generated by examining the experimental outputs based on the independent variables controlling the FDM process and the responses of overall dimensional error (shape accuracy) and fabrication time. These algorithms (Mirjalili *et al*. 2016a, 2016b, 2017a, 2017b); were developed and implemented in Mathworks® Matlab® environment. The algorithm-specific parameters were properly adjusted. The hypervolume indicator was adopted to rigorously compare the algorithms for their performance. This metric was selected owing to its capability of simultaneously testing coverage, pertinence and uniformity of the non-dominated solutions covering a Pareto-front. From the experiment a custom response surface design was created to introduce curvature and represent the variables in continuous form. Contour plots were generated to study the effect of FDM parameters on the two responses of fabrication time and overall dimensional error. According to the statistical analysis, the regression models formulated to correlate the independent variables to the responses were statistically validated. Statistical analysis was based on the examination of normal probability plots referring to the two regression models. According to their *p*-values it was judged that these models may serve as objective functions to optimize the bi-objective problem. The range of parameters for building the search space for the algorithms was the same as per the levels of the response surface experiment based on the original orthogonal array (L_9) experiment. Robust design of the experiments was used for the experimental procedure. Control factors and their levels are shown in Table 1. As mentioned above some

Table 3 Experimental results for overall dimensional error (mm) and fabrication time (min)

Number of experiments	Overall dimensional error (mm)	Fabrication time (min)
1	0.116	37
2	0.093	25
3	0.040	19
4	0.142	68
5	0.208	40
6	0.169	29
7	0.155	63
8	0.161	47
9	0.234	37

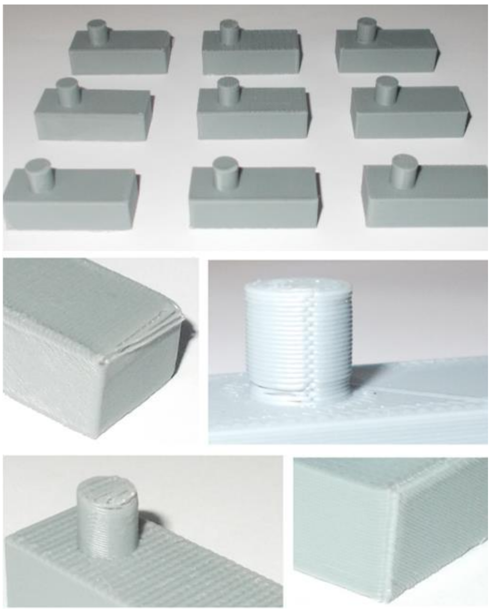

Fig. 1 Fabricated parts according to L9 Taguchi OA

parameters held constant: melted temperature at 275 °C, bed temperature at 80 °C and raster angle at 45°. The diameter of heated nozzle was 0.4 mm, and ABS filament diameter was 1.75 mm. Finally, printing speed is defined by the software parameter (high quality for all the experiments).

Taguchi design uses orthogonal arrays (OAs) in order to perform an experiment. Orthogonality means that all the combinations of the parameter levels appear at each pair of columns of the array. The L_9 orthogonal array is used as shown in Table 2. Experimental results for the two objectives are summarized in Table 3.

Zortrax® M200 desktop 3D printer was use with a build volume of X (200 mm), Y (200 mm) and Z (180 mm). The layer resolution ranges between 90 to 390 microns. ABS material is used for building the models. Dimensional accuracy measurements were performed by a digital caliper. Fabrication time (min) was extracted by the corresponding log files. Nine test parts were built according to L_9 orthogonal array.

Fig. 1 shows the nine experimental specimens as well as their quality issues related to the FDM process. The dimensions measured were the base of the test part, i.e., X:35 mm, Y:15 mm, and Z:10 mm. Dimensional error was obtained with reference to the nominal dimensions whilst the mean of the overall result for dimensional error corresponding to X, Y and Z axes, was finally calculated to formulate the first optimization objective.

2. Experimental results and statistical analysis

Analysis of the experimental results was carried out using MINITAB R17. Statistical analysis involved the analysis of variance and the generation of contour plots corresponding to the full quadratic models created to predict the two objectives of the overall dimensional error and fabrication time. With reference to ANOVA analysis significant factors as well as significant interactions among them, were estimated. *F* and *P* values are important indicators to check whether a factor is significant to affect a response. Probability of *F* value greater than calculated *F* value due to noise is indicated by *p*-value. If *p*-value is less than 0.05, significance of corresponding term is established. For lack of fit, *p*-value must be greater the 0.05. An insignificant lack of fit is desirable, because it suggests that any term excluded from model is not significant and that the generated regression model fits well. Based on analysis of variance (ANOVA) conducted, full quadratic models for overall dimensional error and fabrication time where found to be suitable for estimating the objectives. The t-test was performed to determine the individual significant terms at 95% of confidence level whilst final response surface equations in uncoded form for overall dimensional error (XYZ accuracy), and fabrication time (Time) are given in Eqs. (1) and (2) respectively. The coefficients of determination (R^2) which indicate the percentage of total variation in the objectives, explained by the terms in the models, were found equal to 96.67% and 97.77% for overall dimensional error (XYZ accuracy), and fabrication time (Time) respectively.

$$\text{XYZ-Accuracy: } =0.157+ 0.00114 *x1- 0.113\, x2- 0.00368* x3- 0.000177* x1^2- 1.13* x2^2+ 0.000148* x3^2+ 0.0396*x1*x2. \quad (1)$$

$$\text{Time: } =40.8+ 2.241*x1-284*x2+2.39*x3-0.034*x1^2+483*x2^2-0.0608*x3^2-2.56*x1*x2 \quad (2)$$

The “Anderson-Darling” normality test results are presented in Fig. 2 for respective residue. *P*-value of the normality plots are far beyond 0.05 hence signifying that residues follow the normal distribution. The curvature owing to the complexity of the optimization problem with regard to the independent variables controlling the fused deposition modelling (FDM) process has been examined by generating the contour plots corresponding to the customized response surface design with reference to the initial L_9 Taguchi orthogonal array. The contour plots have been generated by selecting a pair of two out of the three total independent variables referring to each of the two optimization objectives. Fig. 3 illustrates the three contour plots referring to the objective of overall dimensional error (XYZ accuracy). In these plots the objective is treated as “smaller is better” case since dimensional error should be minimized. Fig. 3(a) shows the effect of deposition angle and infill ratio parameters on the overall dimensional error. It can be observed that the overall dimensional error is reduced when operating the 3D printing process using low deposition angle, i.e., 0° with a high infill ratio, i.e., higher than 20%. Similar observation is shown when examining deposition angle and layer thickness (see Fig. 3(b)). The objective of overall dimensional error (XYZ accuracy) is minimized when using low deposition angle and high layer

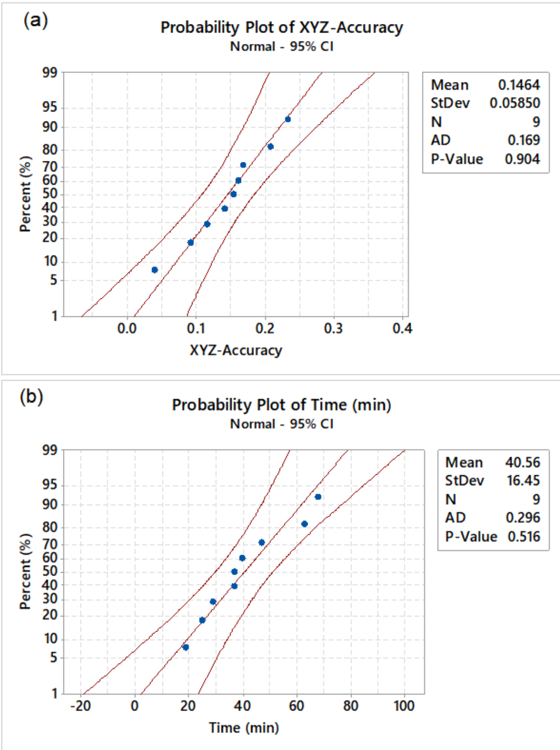

Fig. 2 Normal probability plot of residual at 95% of confidence interval: (a) overall dimensional error (b) fabrication time

thickness. The curvature owing to the effect of layer thickness and infill ratio on the response of overall dimensional error is the most complex compared to those reported for the pairs between deposition angle / infill ratio and deposition angle / layer thickness. It can be seen from the corresponding contour plot illustrated in Fig. 3(c) that the optimal region for setting these two parameters with respect to the minimization of the overall dimensional error is the region where infill ratio is adjusted between 15% and 22% while simultaneously using a value for layer thickness from 0.13 mm to 0.19 mm.

There is also a narrow region where the overall dimensional error reduces for setting layer thickness between 0.26 mm and 0.28 mm while selecting a value for infill ratio parameter ranging between 26% and 30%. The results reported above show that there are discrete ranges from which values for the FDM parameters should be selected and selections should be such that kinematics of the 3D-printer referring to X, Y and Z axes should be facilitated to sustain a low dimensional error. The results for studying the effect of FDM parameters on fabrication time have been examined with reference to the corresponding contour plots shown in Fig. 4. According to Fig. 4(a) fabrication time is minimized if higher values for infill ratio are set with the adjustment of low deposition angle. As far as the pair of FDM parameters between deposition angle and layer thickness is concerned, lower values for the former and higher values for the latter seem to reduce the fabrication time (Fig. 4(b)). When studying the effect on layer thickness and infill ratio on fabrication time a range of values between 15% and 30% for infill ratio and a range of values

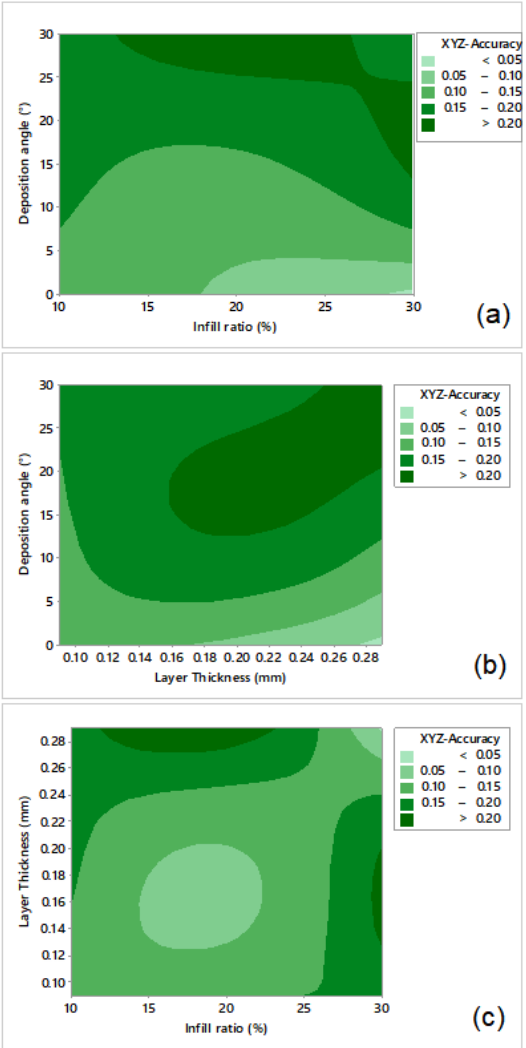

Fig. 3 Contour plots for studying the effect of FDM parameters on the overall dimensional error [XYZ accuracy]: (a) deposition angle / infill ratio, (b) deposition angle / layer thickness, (c) layer thickness / infill ratio

between 0.17 mm and 0.26 mm seems to minimize the response. However, moving towards the solution space suggesting the highest values for both parameters, i.e., 0.28 mm for layer thickness and 30% for infill ratio optimizes the fabrication time as expected.

3. Implementation of population / swarm -based evolutionary algorithms

The responses of overall dimensional error and fabrication time formulate a dual-objective optimization problem referring to FDM parameters. Both objectives are to be minimized. These

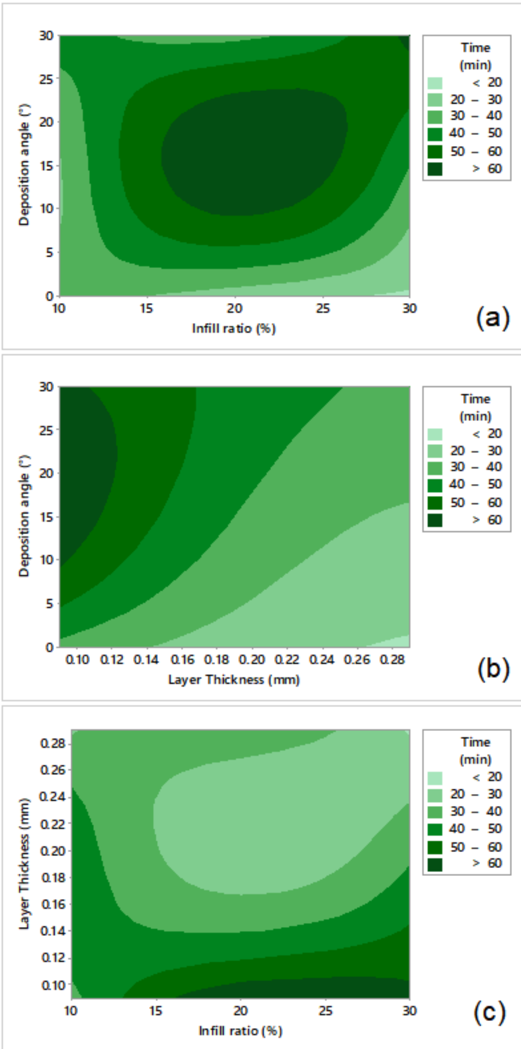

Fig. 4 Contour plots for studying the effect of FDM parameters on the fabrication time [Time]: (a) deposition angle / infill ratio, (b) deposition angle / layer thickness, (c) layer thickness / infill ratio

two objectives suggest an inherent trade-off between them since productivity is opposed to quality and vice versa owing to their different scope in production lines. Evolutionary algorithms seek for several solutions in a search domain by generating random candidates for a given problem. These solutions are known as non-dominated solutions. The set of candidates is subsequently improved until one or more termination criteria are met. Improvement may be considered as finding an accurate approximation of the global optimum in contrast to the initial random guesses. This behavior makes evolutionary algorithms advantageous under several aspects such as problem independency, derivation independency, local optima avoidance, and simplicity. Although, a problem's nature is not a concern, its representation constitutes a key step when employing evolutionary algorithms. Local optima avoidance is high owing to the stochastic behavior of evolutionary algorithms. Should an evolutionary algorithm gets trapped to a local optimum, its corresponding stochastic operator leads to random changes in the solution thus, eventually escaping from the local optimum. Even if there is no guarantee for resolving this issue entirely, stochastic algorithms have much higher probability to escape from local stagnation compared to deterministic approaches. A perfect approximation of the global optimum cannot be guaranteed, yet; running an evolutionary algorithm several times increases the probability of obtaining a better solution. Although evolutionary algorithms found in literature can effectively solve several challenging problems of the technical world, the "No Free Lunch" theorem (Russell *et al*. 1998, Reynolds 1987, Zitzler and Thiele 1999, Ded 2001) leaves room to researchers for continuously suggesting new algorithms. According to "No Free Lunch" theorem, all algorithms perform almost equal when applied to solve most of the optimization problems. This implies that an algorithm may exhibit high efficiency in solving a specific set of problems, as it may also occur ineffective on solving others.

Multi-objective grey-wolf optimizer – MOGWO is a population-based algorithm that simulates the behavior in terms of leadership hierarchy of grey-wolves. In engineering computation four types of grey wolves; alpha; beta; delta and omega are distinguished. Moreover, three types of hunting techniques are followed as major steps by the grey-wolves; prey searching; prey encircling (trapping) and attacking. These steps are also the computational steps for conducting optimization to a problem with this algorithm. Grey-wolves use to live in packs consisting of 5 to 12 grey-wolves in average. They have a very strict social hierarchy starting from alphas, which are a male and a female grey-wolf. Alphas are responsible for decision making when it comes to hunting; sleeping place; wake time; and so on. These decisions should be followed by the rest of grey-wolves in the pack. A more "democratic" behavior about the living behavior of grey-wolves has also been observed where alphas may follow the rest of the wolves in the pack. Alpha wolves are those who dominate in their corresponding packs whilst they are the only ones allowed to mate. Surprisingly, alpha wolves are not necessarily the strongest members in a patch but the best in managing and strategic decision making. This implies that discipline and organization is much more essential than strength at least when it comes to grey-wolves. Second in hierarchy come the "beta" grey-wolves. The "betas" act as advisors to alphas and help them in decision making as well as other pack activities. Betas may be males or females whereas they are probably the best candidates to be alphas, should an alpha wolf pass away or grows too old. Even though a beta wolf should respect an alpha one, a beta may command the rest low-level wolves, as a discipliner. Thus, the beta emphasizes alpha's commands to the whole pack and feedbacks to alpha. Omega grey-wolves are the lowest in hierarchy. The lowest ranking grey-wolves are "omegas". Omegas undertake the role of scapegoats. Omega wolves always submit to all the rest dominant wolves and they are the last ones allowed to eat. Though it seems that omegas are not just as important individuals in the pack as alphas or betas, it has been observed that the whole pack can face internal fighting and problems in case of losing an omega owing to the venting of violence and frustration of all wolves by the omegas. This contributes to the entire pack's satisfaction and maintains the dominance structure. A grey-wolf other than alphas, betas and omegas is a "delta". Delta grey-wolves report to alphas as well as betas, yet; they dominate omegas. Scouting wolves, sentinels, hunters and caretakers are fall to this category. They watch the bounds of their territory and warn the pack for imminent dangers. All engineering computation steps and programming modules corresponding to the steps for executing MOGWO algorithm are reported in Mirjalili *et al*. (2016a). The multi-objective ant-lion optimization algorithm – MOALO simulates the hunting behavior of antlions found in nature. There are five steps for hunting a prey such as the random walk (scouting) of ants, trap building, ant trapping, prey catching and trap rebuilding. Technically the MOALO simulates the interaction of antlions and ants as a population-based heuristic whereas optimal solutions are approximated by initializing a group of random solutions. The main goal of ants is to explore the search space. They are supposed to move around the search space by taking a random walk. The antlions maintain the best position obtained by the ants and guide the search of ants towards promising regions of the search space. The general steps of MOALO for exchanging information among antlions and ants and gradually reaching global optimum according to the natural procedure stated above are the following:

- Random initialization of a few ants as main search "agents".
- Ant fitness evaluation regarding the objective function. c. Random walk of ants around the antlions in the search space.
- The population of antlions is never evaluated. In fact, antlions assumed to be on the location of ants in the first iteration and relocate to the new positions of ants in the rest of iterations if the ants become better.
- There is one antlion assigned to each ant and updates its position if the ant becomes fitter.
- There is also an elite antlion which impacts the movement of ants regardless of their distance.
- If any antlion becomes better than the elite, it will be replaced with the elite.
- Steps *b* to *g* are repeated until stopping criteria are met. The mathematical model and programming modules proposed for each of these steps are reported in Mirjalili *et al*. (2017a).

MOMVO algorithm (Mirjalili *et al*. 2017b) adheres to the principles of some cosmological theories suggesting that multiple universes exist and simulates their interaction through white hole, black hole and worm hole. According to Physics objects may be transferred form a universe via a tunnel from a white hole towards a black hole. As regards worm holes, they are capable of moving objects form the "boundaries" of a universe to the "boundaries" of another without the presence of a white or black hole. MOMVO is an evolutionary algorithm and as such it belongs to the population-based heuristics. Optimization procedure initializes a set of candidate solutions. Each candidate solution is a "universe" whilst variables are analogous to "objects" in the universe. MOMVO deploys its specific operators to combine solutions and distinguish elite ones. To achieve combination among solutions white and black holes are randomly generated in the "universes" causing the movement of objects. MOMVO evaluates an objective function as it occurs to all heuristics. MOMVO employs also the inflation rate which is one of MOMVO's algorithm-specific parameters and simulates the growing speed of a "universe" computed proportional to the objective function. In other words, inflation rate is the objective value attained by evaluating the objective function for a given "universe". In MOMVO when inflation rate increases a higher probability occurs for white holes to improve solutions. On the contrary existence of black holes is inversely proportional to inflation rate causing the variables' flow from worse "universes" to better ones. By incorporating the features in MOMVO any solution can contribute to the generation of new solutions as opposed to crossover that mates only two parents for producing a child. In addition, white and black holes maintain exploration of solution space owing to changing solutions in a sudden sense. The "elitistic" behavior of MOMVO keeps the best solutions obtained so far whereas worm holes generate tunnels between the best solution and any other solution to pass information and this finally aims to improve exploitation in MOMVO.

Dragonflies are considered as small predators hunting almost all other smaller insects found in nature. Nymphs also predate on other marine insects or small fishes. What is interesting about dragonflies is their unique swarming behavior. Dragonflies swarm only for two major goals: hunting and migrating. The former is known as the static (feeding) swarm whereas the latter is

Table 4 Statistical results obtained by algorithms for overall dimensional error (mm) and fabrication time (min)

MOEA	Obj.	Statistical results			
		Best	Mean	Worst	StDev
MOGWO	1*	0.0000	0.0371	0.0812	0.0351
	2**	16.040	16.8178	22.7338	1.1112
MOMVO	1*	0.0000	0.0446	0.0802	0.0277
	2**	16.046	16.6383	16.6383	0.2924
MOALO	1*	0.0000	0.0549	0.0755	0.0271
	2**	16.097	16.5539	16.5539	0.7736
MODA	1*	0.0001	0.0636	0.0810	0.0217
	2**	16.041	16.3563	16.3563	0.4947

* XYZ accuracy (mm)

**Fabrication time (min)

known as the dynamic (migratory) swarm. When it comes to static swarm dragonflies formulate small groups flying back and forth over a small region to hunt other preys such as butterflies and mosquitoes (Wikelski *et al*. 2006). Local movements and abrupt changes in the flying path are the major characteristics of a static swarm. When it comes to dynamic swarms a vast number of dragonflies migrate towards long-distanced directions (Russell *et al*. 1998). These two swarming behaviors implemented to MODA algorithm simulate the two mandatory attributes of optimization algorithms: exploration and exploitation. Dragonflies formulate subswarms to fly over several territories in a static swarm, which is the objective of the exploration phase. In addition, if a static swarm is formulated by a larger number of dragonflies flying along one specific direction facilitates the exploitation phase. The behavior of swarms follows three primitive principles (Reynolds 1987):

- Separation - referring to the static collision avoidance of individuals from other individuals in the searching neighborhood,
- Alignment - this principle indicates velocity matching of individuals to that of other individuals in the searching neighborhood and
- Cohesion - referring to the tendency of individuals towards the center of mass of the searching neighborhood.

Since survival is the major objective of any type of swarm or tribe, all individuals (candidate solutions) ought to be attracted towards food sources and avoid outward enemies. Exploration and exploitation phases as well as major steps that MODA algorithm deploys to solve an optimization problem are mathematically modelled and reported in Mirjalili *et al*. (2016b).

MOGWO, MOALO, MOMVO and MODA algorithms were applied to solve the dual objective optimization problem with the objectives of overall dimensional error and fabrication time. All algorithms were executed 10 times and their statistical outputs were examined to judge their efficiency. Table 4 summarizes the best (min) the worst (max) the mean and standard deviation of these results obtained by these simulations.

The algorithms run by determining 20 individuals and 1000 generations thus, 20000 function evaluations. The algorithm-specific parameters were constrained according to the

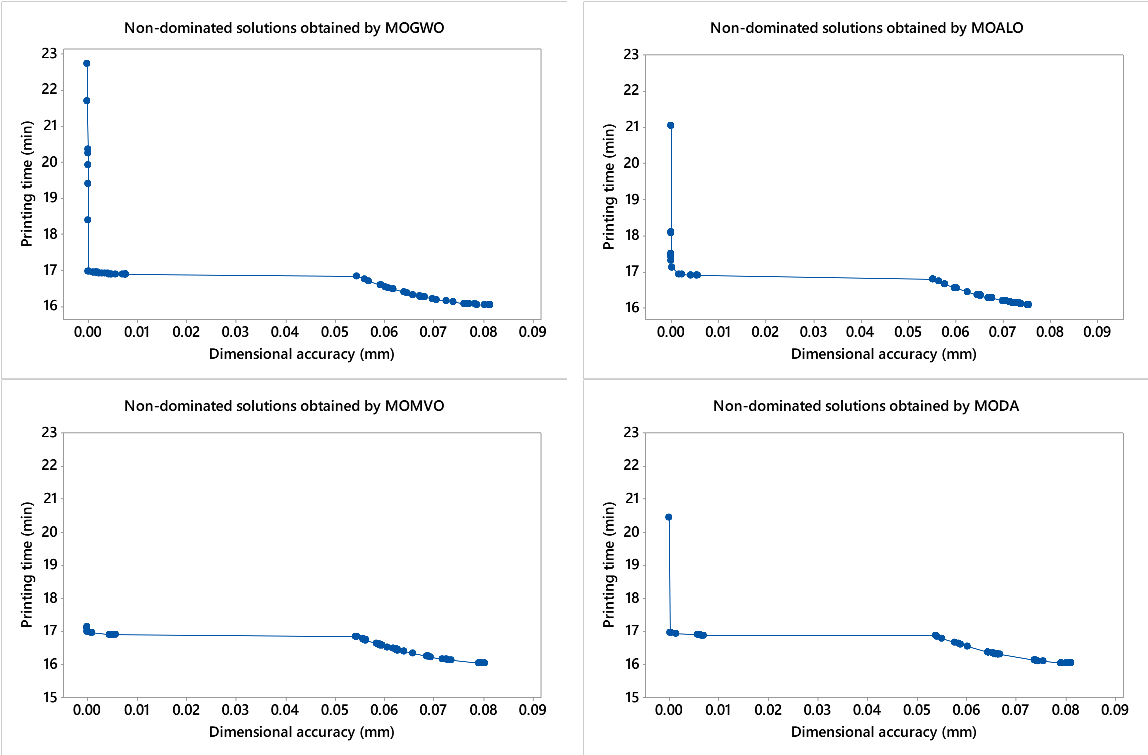

Fig. 5 Pareto fronts obtained by evolutionary algorithms

recommendations of the references reported for each of the algorithms tested. The range for FDM parameters was the same as per the experiment's low and high levels. All algorithms managed to generate promising non-dominated solutions to optimize the problem. This conclusion is supported by the small differences observed in the results for the two objectives. The minimum result for the overall dimensional error was found equal to 0.0000 mm for 0º deposition angle, 0.28 mm layer thickness and 10.37% infill ratio. The best output for fabrication time was found equal to 16.040 min. This result achieved by MOGWO algorithm. The results for fabrication time equal to 16.046 min, 16.097 min and 16.041 min were achieved by MOMVO, MOALO and MODA algorithms respectively. These outputs for fabrication time were observed for deposition angle equal to 0º, layer thickness equal to 0.29 mm and 30% for infill ratio. These outputs are in total agreement with the experimental results observed by generating the contour plots regarding the levels of FDM independent process parameters. It is also observed that the parameters of deposition angle and layer thickness facilitate both optimization objectives whilst the trade-off seems to be observed in infill ratio. The best mean output for the objective of overall dimensional error was found equal to 0.0371 for MOGWO algorithm. The largest mean output for overall dimensional error was found equal to 0.0636 for MODA algorithm. With reference to this result MOGWO seems to outperform the rest algorithms in terms of the range of results concerning the overall dimensional error. However, MODA algorithm exhibited the best standard deviation for the results of overall dimensional error. With reference to this result MODA seems to outperform the rest algorithms in terms of the variability of results concerning the overall dimensional error.

Table 5 Results for hypervolume and area indicators for algorithms

Algorithm	HV (mm^3)	Area (mm^2)
MOGWO	1.352	37.103
MOALO	1.332	37.072
MOMVO	1.269	36.877
MODA	1.364	37.078

Analogous observations can be commented for the objective of fabrication time. By observing the Pareto fronts for the non-dominated solutions achieved by MOGWO, MOALO, MOMVO and MODA algorithms, significant differences in terms of coverage and spacing are found. However, in order to compare the non-dominated set of solutions obtained using MOGWO, MOALO, MOMVO and MODA algorithms the hypervolume (HV) performance indicator proposed by Zitzler and Thiele (1999) is adopted in this work. Hypervolume is a metric that calculates the volume, - or area in the case of bi-objective problems - of the objective space covered by the members of a Pareto optimal set. Normally, a higher value for hypervolume or area is preferable because it indicates larger coverage in terms of the search domain. However, better performance is decided upon the nature of objectives under question. In this work both objectives should be minimized thus the percentage of non-dominated solutions should be close to the origin to satisfy both objectives simultaneously. In this work the method suggested in Deb (2001, 2002) has been adopted to develop a script hosted to a CAD/CAM system's open application programming interface (API) and applied for computing the hypervolume and area. It should be mentioned here that since the script supports also three-objective optimization problems, a Z-height equal to 0.01 mm for extruded instances in CAD/CAM software was programmed. Thereby, the extruded instances are automatically designed using as width, length and height (all dimensions are converted to mm) the values for objectives corresponding to 1st, 2nd and a 3rd "dummy" objective with the value of 0.01mm for the extruded Z-distance. All extruded instances are created by using the same reference axis system that represents the origin of the Pareto front in CAD software. The results for all algorithms tested are shown in Table 5.

It is observed that the hypervolume of the Pareto-front obtained using MOMVO is equal to 1.269 mm^3 whilst its corresponding area is equal to 36.877 mm^2. Based on this result one can support that MOMVO's Pareto front provides solutions closer to the origin as opposed to the rest of the algorithms. Indeed, MOMVO is the only algorithm attaining lower fabrication times with good spread and coverage for its results corresponding to overall dimensional error. The rest algorithms provide some fabrication times higher than 20 minutes which is not advantageous. On the other hand, MOGWO seems to provide the largest percentage of solutions close to the origin. All solutions obtained by the algorithms are uniformly distributed to their Pareto fronts. Fig. 5 shows the Pareto fronts obtained by the algorithms.

4. Conclusions

In this work a multi-objective optimization problem based on the fused deposition modeling process has been presented. Taguchi method was first employed for the experimental procedure design and nine test parts were built according to L_9 orthogonal array. The examined process parameters were the deposition angle, layer thickness, and infill ratio each one having three levels. Infill pattern was constant to honeycomb selection. Fabrication time of ABS (Acrylonitrile-Butadiene-Styrene) 3D printed specimens was measured during experiments and analyzed by using Analysis of Means (ANOM) and Analysis of Variance (ANOVA) techniques. Shape accuracy was measured by considering the parts' dimensions in X, Y and Z axes and expressed as the overall error for control. Regression models were developed to use them as objective functions for a group of multi-objective optimization algorithms. Multi-objective Greywolf (MOGWO), multi-objective antlion (MOALO), multi-verse (MOMVO) and multi-objective dragonfly (MODA) algorithms where implemented to simultaneously optimize the bi-objective FDM optimization problem. To evaluate the algorithms and judge superiority with reference to the non-dominated solution sets obtained the hypervolume (area) indicator was adopted. It was verified that algorithms perform differently to the problem formulated for optimizing the FDM process. The statistical results (best, worst, mean and standard deviation) validate the no-free-lunch theorem suggesting than no algorithm can handle all problems with the same accuracy and efficiency. These algorithms may also be applied to solve the optimization problems pertaining to other RP processes such as stereolithography, selective laser sintering, laminated object manufacturing, 3D printing, solid ground curing, etc.

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