Proceedings of the 2017 Winter Simulation Conference
W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer, and E. Page, eds.

ITERATIVE MULTICRITERIA SIMULATION AND PROTOTYPING OPTIMIZATION IN MANUFACTURING

Esmeralda Niño-Pérez
César A. Rivera-Collazo
Mauricio Cabrera-Ríos

The Applied Optimization Group
Industrial Engineering Department
University of Puerto Rico at Mayagüez
Mayagüez, PR 00681, USA

Yaileen M. Méndez-Vázquez

Mechanical, Industrial, and Manufacturing
Engineering School
Oregon State University
Corvallis, OR 97330, USA

ABSTRACT

In this work a multicriteria simulation optimization method previously developed in our research group was applied to the experimental optimization of a 3D printed prototype. Both, simulation and prototyping, share the objective of providing as much information as possible about a product before its actual manufacturing. The prototype is an interlocking device that can be assembled without fastening devices or substances and reassembled into different planar assemblies. The design of the prototype considers two conflicting criteria simultaneously: maximal flexural strength and minimal mass. Multicriteria simulation optimization allows to manipulate a set of design variables to identify configurations with the best possible balances among both criteria. This method consists of an iterative framework based on experimental design and Pareto efficiency conditions. The aim of this work is to show the potential of the method beyond its initial intended use in simulation to approach truly experimental work.

1 INTRODUCTION

3D printing technology has evolved in the past few years to take an important role in manufacturing processes, not only in the early stages of the product design, but also in the making of final parts, molds, and tools (Rayna and Striukova 2016). The use of 3D printing in manufacturing became attractive for its flexibility and precision to create parts with complex geometries, low fabrication cost, and the ability to easily implement changes in the design as a result of the linked concept in which it works, better known as computer-aided design (CAD) (Mearian 2014; Gibson et al. 2015; Ransikarbum et al. 2017). This last property makes feasible and convenient (i) the manipulation of multiple design variables and (ii) the assessment of multiple performance measures simultaneously for the design and manufacturing of a part. An optimization procedure with (i) and (ii) as key capabilities, greatly enhances the quality of information that can be obtained from a 3D printed prototype or an actual product.

In the literature, several works address the problem of multicriteria optimization in manufacturing processes developing algorithms and heuristic methods for the decision-making process involving design variables (Cabrera-Ríos et al. 2002; Castro et al. 2003; Cabrera-Ríos et al. 2004; Castro et al. 2004; Castro et al. 2005; Pohlak et al. 2010; Rodríguez-Yañez et al. 2014; Ransikarbum et al. 2017; Schatz et al. 2017). However, in most of the cases, the incorporation of these methods is demonstrated using simulation scenarios and do not show the implementation of the method in a physical experimental scenario where additional sources of non-controllable variability are present (Pohlak 2010; Rodríguez-Yañez et al. 2014; Ransikarbum et al. 2017; Schatz et al. 2017).

In this work, the design and manufacturing of an interlocking device is addressed using 3D printing technology and a novel multicriteria optimization (MCO) method proposed in a previous work of our

978-1-5386-3428-8/17/$31.00 ©2017 IEEE

group (Niño-Pérez et al. 2017). The referenced optimization method was used for the setup of the design variables, considering two performance measures as objective functions: maximization of flexural strength and minimization of the total mass of the part. Maximization of the first objective would allow withstanding load, while minimization of the second one would make fabrication feasible with little material –for example as little as that available in a single PET water bottle to be recycled. With the implementation of the method, the Pareto-efficient frontier was obtained, which represents the set of candidate configurations with the best balances for the defined conflicting performance measures. The part to be 3D printed is an interlocking device that can be assembled without the use of fastening devices/substances and that can be reassembled and reconfigured for different planar parts –for instance, to create a stepping stone for the garden. The details of the part design, experimental design, and results of the optimization implementation will be discussed in the following parts of this manuscript.

The remaining sections of this work are organized as follows: Section 2 presents a literature review focused on the implementation of multicriteria optimization methods for the design and manufacturing process of prototypes using 3D printing technology in physical experimental scenarios; Section 3 describes the theoretical background and terminology associated to the method implemented in this study; Section 4 presents the description of the case study and the results of the application of the MCO method; Finally, conclusions and future work are discussed in Section 5.

2 LITERATURE REVIEW

MCO has been a long-standing topic of interest in the field of engineering design. Its significance lies in the fact that virtually all real manufacturing problems are multicriteria in nature, calling for their simultaneous consideration and compliance in the presence of conflict. This type of problems can be approached through the identification of the best compromising set of solutions that form the so-called Pareto-efficient frontier (Marler and Arora 2004; Rodríguez-Yañez et al. 2014; Niño-Pérez et al. 2017). Pareto-efficient solutions found in this frontier contain the settings of the decision variables that can be applied onto the manufacturing process/system/product. (Marler and Arora 2004; Rodríguez-Yañez et al. 2014).

On the other hand, additive manufacturing has been one of the manufacturing processes that has significantly benefited from the theory of the MCO. Additive Manufacturing includes 3D printing, which has revolutionized the manufacturing field by allowing the design and testing of complex parts at lower cost than the traditional prototyping methods (Peacock 2014; Lu et al. 2015). Given the advantages that 3D printing offers, it has taken prominence in manufacturing from early stages of the design process of a part –as prototyping- through the final one of it –as production- (Mearian 2014; Peacock 2014; Lu et al. 2015; Asadi-Eydivand et al. 2016a; Asadi-Eydivand et al. 2016b).

Several works have been developed in the literature to address the decision-making process of product design involving 3D printers and considering multiple performance measures simultaneously (Irisarri et al. 2010; Ancau and Caizar 2014; Clark et al. 2014; Stankovic et al. 2015; Asadi-Eydivand et al. 2016a; Asadi-Eydivand et al. 2016b; Marinić-Kragić et al. 2016). However, only few of them transcend from the simulation application to the physical experimental implementation (Ancau and Caizar 2014; Clark et al. 2014; Asadi-Eydivand et al. 2016b). Knowledge related to the physical implementation of multicriteria optimization methods for the design and manufacturing of a prototype is scarce, which is part of the aim of this manuscript: show the applicability of the method for truly experimental work and the performance of the method under physical experimental conditions.

3 METHOD

The optimization strategy used in this work integrates the use of experimental design and metamodeling techniques to address the design and manufacturing of a prototype as a multicriteria optimization problem (Niño-Pérez et al. 2017). Figure 1 shows the scheme of the implemented algorithm in its original fashion focused on simulation-optimization. The main details of the method adapted to a physical experimental scenario are explained below following the steps listed in Figure 1 (labels $\boxed{\text{number}}$):

The method starts with the development of an experimental design (DOE) used to setup the design and processing variables of the prototype. A prototype was 3D printed for each design point ($\boxed{1}$-$\boxed{2}$) and an initial incumbent solution is obtained ($\boxed{3}$). The incumbent solution corresponds to the Pareto-efficient frontier that represents the set of best compromises between all performance measures (PMs) in the experiment. With the experimental runs at hand, one metamodel per performance measure is obtained ($\boxed{4}$) and used to make predictions in the discretized experimental region ($\boxed{5}$). Potentially Pareto-efficient points are detected ($\boxed{6}$-$\boxed{8}$). These predicted points are then simulated and joined with the incumbent solution to determine if a new Pareto-efficient frontier has been found ($\boxed{9}$). If the Pareto-efficient frontier does not change, then the incumbent solution is reported and no more iterations are performed. Otherwise the incumbent solution is updated and the newly-simulated points are added to the set of available points and a new iteration begins with the constructions of new metamodels ($\boxed{4}$). In detailed fashion, the method is as follows:

Initialization

- Set $k = 0$
- Initial DOE: Run a first design of experiment D_0 with n simulation runs considering all L variables and all J performance measures (PMs). Each controllable variable and performance measure must be scaled to fall between -1 and 1 to avoid dimensionality problems.
- Select incumbent: Analyze D_0 to determine which of its points are Pareto-efficient. The Pareto-efficient solution I_0 contains all Pareto-efficient points of D_0.

> *A Pareto-efficient solution will be found when, in the full pairwise comparison with the rest of the solutions, there is no other solution that dominates it in all PMs simultaneously.*

- Set $D_0^{available} = D_0$

Main Iteration

- Update counter $k = k + 1$
- Use $D_{k-1}^{available}$ to fit all J metamodels, $y_j\ [k]$.
- Use metamodels to predict the values of all J objective functions using a grid of $n_k = [G_1 \times G_2 \times \ldots \times G_l \times \ldots G_L]$ points, where G_l is the number of equidistant discrete points for the l^{th} variable. Store these points in a matrix P_k with dimensions $[n_k \times (L + J)]$, where P stands for predicted.
- Analyze P_k to determine which of its points are Pareto-efficient. Store the efficient points in P_k^E (where P stands for predicted and E stands for Efficient).
- Simulate all points in P_k^E. Store the simulated results in a matrix D_k.
- Set $C_k^I = I_{K-1} \cup D_k$, where C stands for candidates and I for incumbent.
- Analyze C_k^I to determine which of the points are Pareto-efficient. Store the efficient points in I_k.

Termination

- Evaluate the stopping criteria. If $I_k = I_{k-1}$, then terminate the algorithm and present the incumbent solution I_k. Otherwise, update $D_k^{available} = D_{k-1} \cup D_k$ and reiterate.

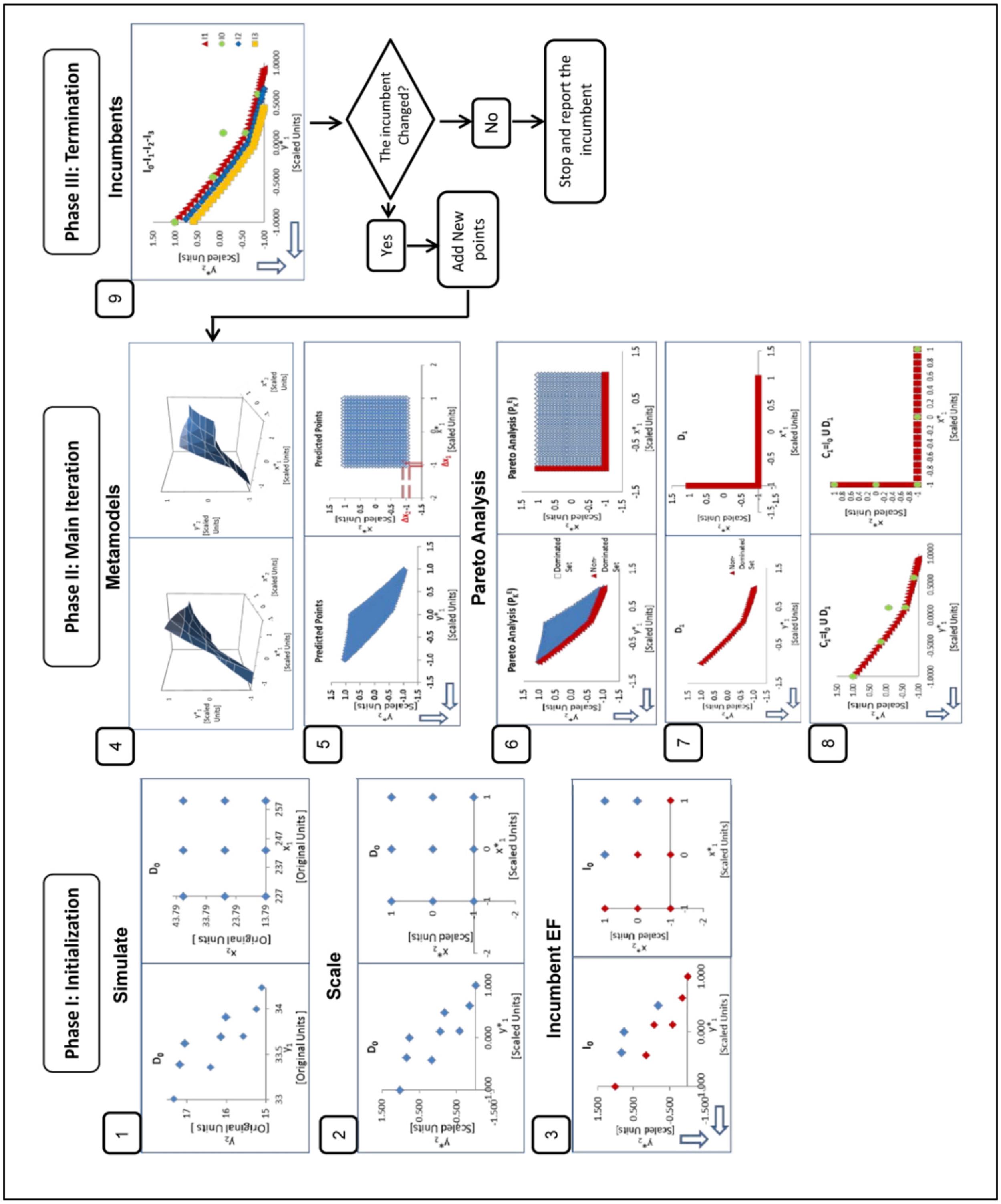

Figure 1: Proposed Multicriteria Simulation Optimization Method. (from Niño-Pérez et al. 2017)

4 EMPIRICAL CASE STUDY: 3D PRINTER PROTOTYPE

In order to obtain a design that considers the performance measures of interest, minimum mass and max-flexural resistance, a DOE was generated as an initial step (Table 1). For the current study a Box-Behnken design with 16 experimental runs was used. The proposed DOE considered three controllable variables (Table 1): (i) cylinder depth –which controls the position of the three protruding cylinders (see Figure 2), (ii) cylinder diameter, and (iii) part thickness. These three were expected to affect flexural strength and overall mass of the part. For each experimental run defined in the proposed DOE, a prototype was produced. The time to 3D print and assemble an entire prototype was about 1 hour.

Table 1: Initial experimental design.

Controllable Variables	**Levels**
Cylinder depth	{0.230, 0.345, 0.460} in
Cylinder diameter	{0.018, 0.030, 0.041} in
Thickness	{0.092, 0.161, 0.230} in

Figure 2 shows the representation of the system for the physical experiment considered in this work. The process consists of the actual 3D printing. Finally, the outputs represent the two selected performance measures for the optimization procedure, flexural strength and mass.

Once the initial DOE was executed and the respective data was collected, the next step was the development of a model for each response based on the information gathered during experimentation. Finally, the proposed optimization method previously described was applied to determine suitable variable settings aiming to maximize the flexural strength and minimize the total mass. The details of each phase are described below.

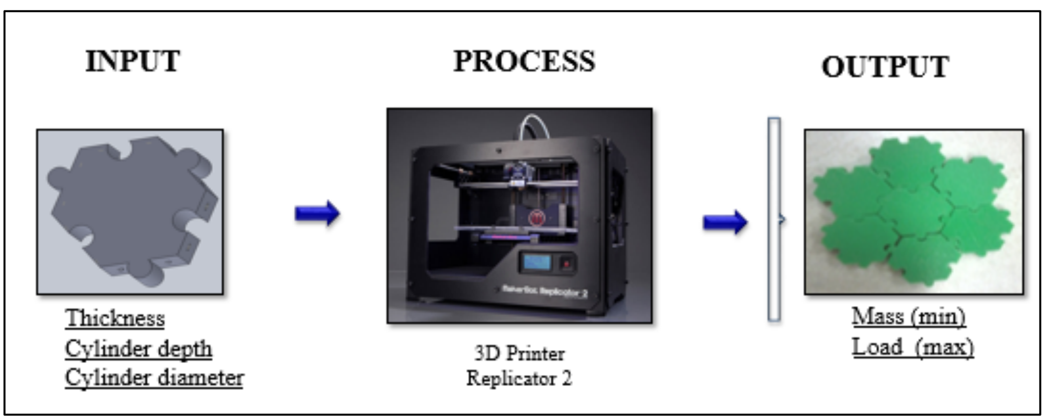

Figure 2: Interlocking device design system representation.

Initialization: A flexural test was performed in each of the produced units to determine the max load (measured in lbf). The measures were made using a Universal Testing Instruments Machine / 5940 Series Single Column Table Top Systems for Low-Force Mechanical Testing / INSTRON. For the evaluation of the max load using the equipment previously described a distributed load was applied as is shown in Figure 3. After the max load was measured, the interlocking device was weighted to determine its mass (measured in g), as shown in Figure 4. The natural variables and the experimental values of the PMs were coded using a linear transformation to make them fall in the range of [-1, 1] as to avoid dimensionality problems (Figure 5). With these coded values the efficient frontier was found, using a MATLAB code presented in Camacho-Cáceres et al. (2015). This efficient frontier became the initial incumbent solution (I_0) as shown in Figure 6. Do notice that, for representation purposes, both PMs are shown as minimization cases. Indeed, any maximization case can be turned into an equivalent minimization case through a suitable linear transformation.

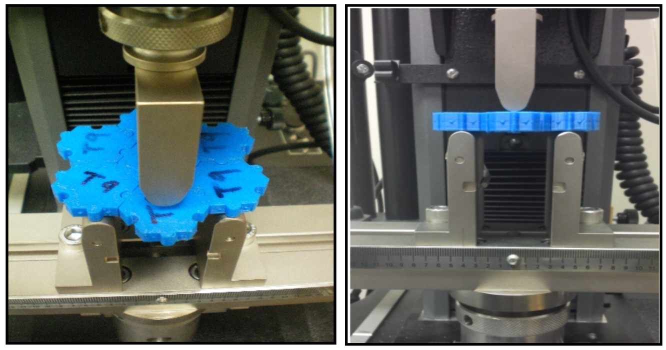

Figure 3: Interlocking device flexural test.

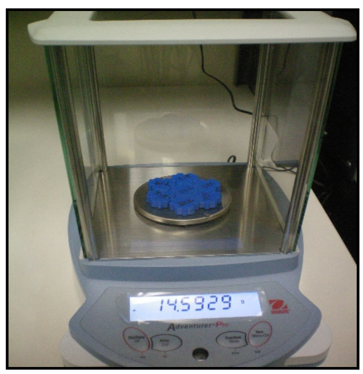

Figure 4: Interlocking device mass measuring process.

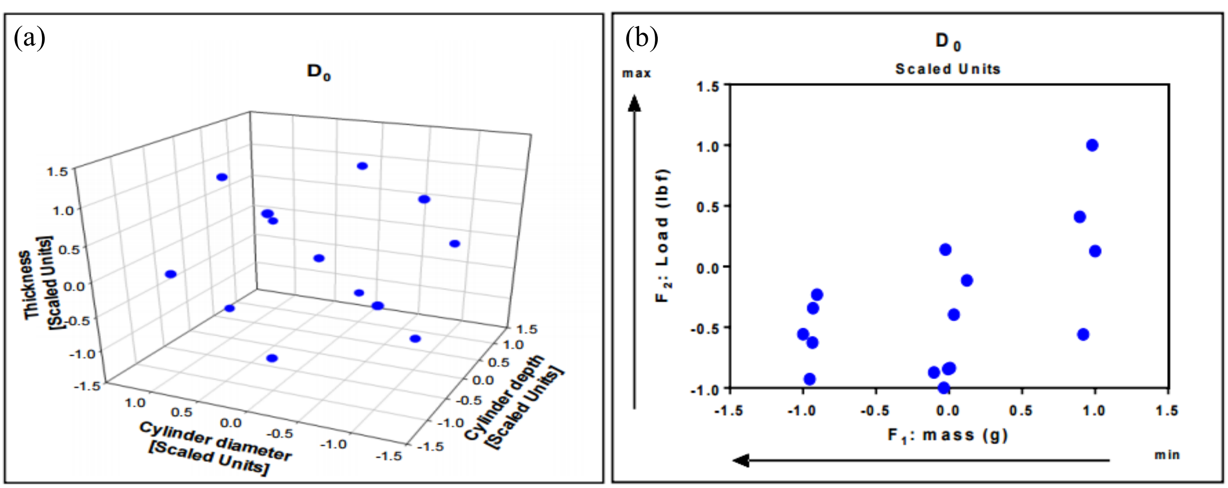

Figure 5: Linear transformation in the range [-1, 1], (a) controllable variables (CV) and (b) performance measures (PMs).

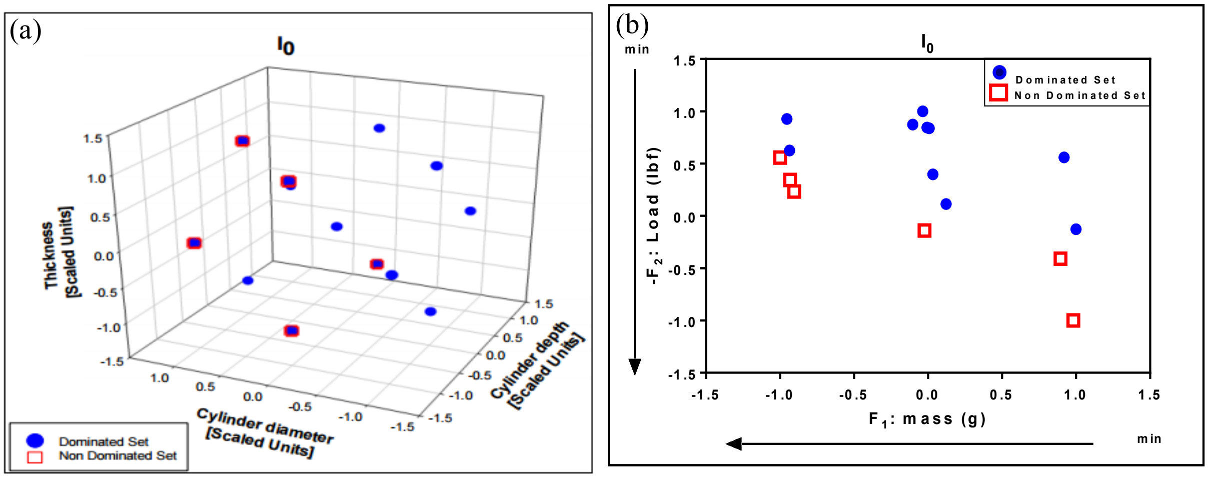

Figure 6: Initial pairwise comparison for the incumbent solution (I_0), (a) controllable variables and (b) performance measures.

Main Iteration: With I_0 at hand, the iterative phase of the algorithm begins. To generate predictions within the experimental region, a second order regression metamodel per PM was constructed using D_0. Predictions were then obtained in these 125 points for both PMs as shown in Figure 7. In turn, these predicted solutions were evaluated to determine the Pareto-efficient ones as shown in Figure 8. The solutions found represent potentially efficient candidates at this point, thus an experimentation is carried out at these attractive points, as shown in Figure 9. With these new points, the incumbent solution I_0 must be revised for Pareto-efficiency. When the comparison was carried out, 3 new points added to the efficient frontier and 4 points of the incumbent solution I_0 were now dominated points as shown in Figure 10. Consequently, these dominated solutions were deleted from the new incumbent solution I_1 as shown in Figure 11. The points of the candidate set D_1 are added to the available points D_0, and the second iteration of the algorithm ensued. The second iteration follows the same structure as before, with the creation of a new set of potential solutions D_2. These combinations were then produced and compared with the incumbent solution I_1 using the Pareto conditions.

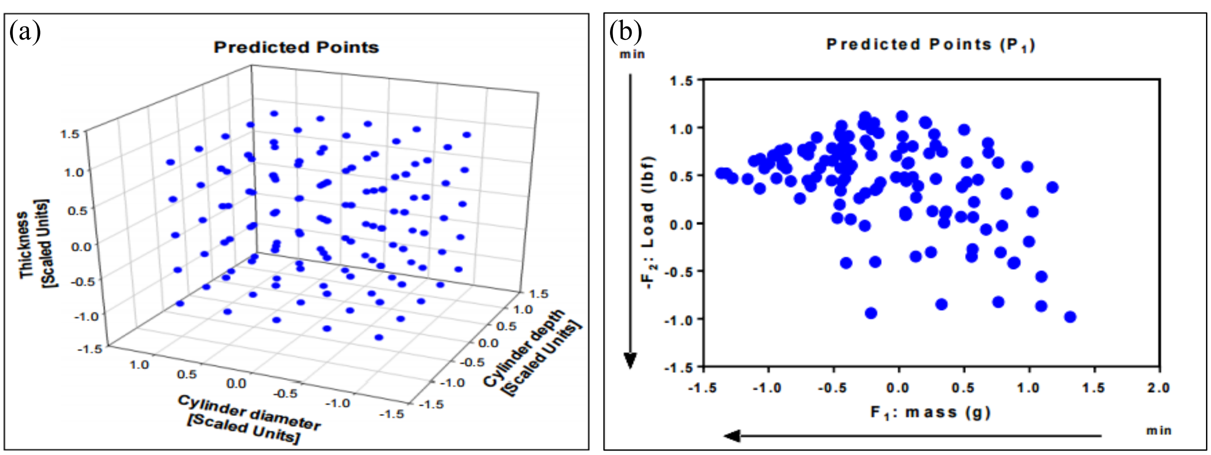

Figure 7: Initial predicted points (P_1), (a) controllable variables and (b) performance measures.

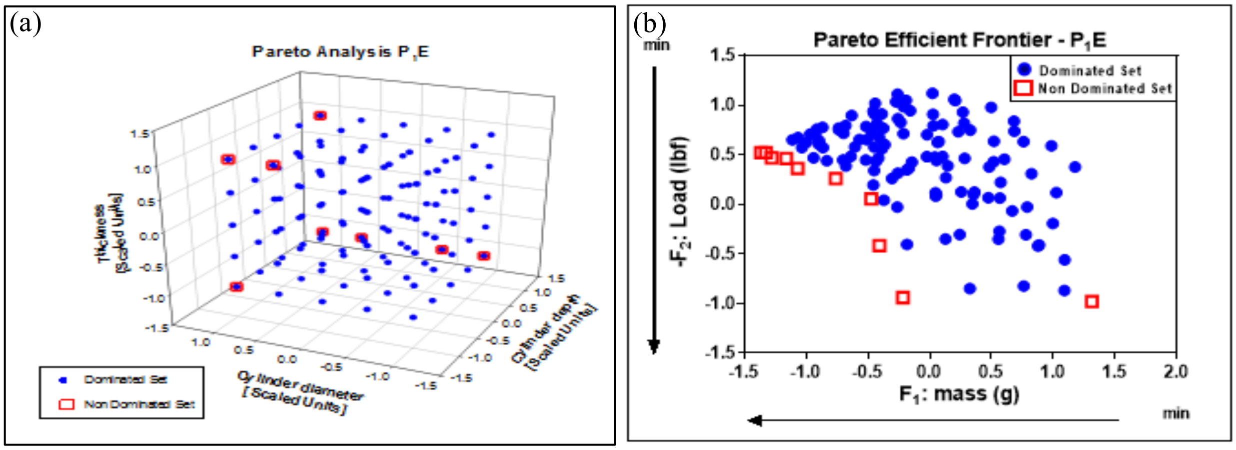

Figure 8: Predicted Points that are Pareto Efficient (P_1^E) in the k=1, (a) controllable variables and (b) performance measures.

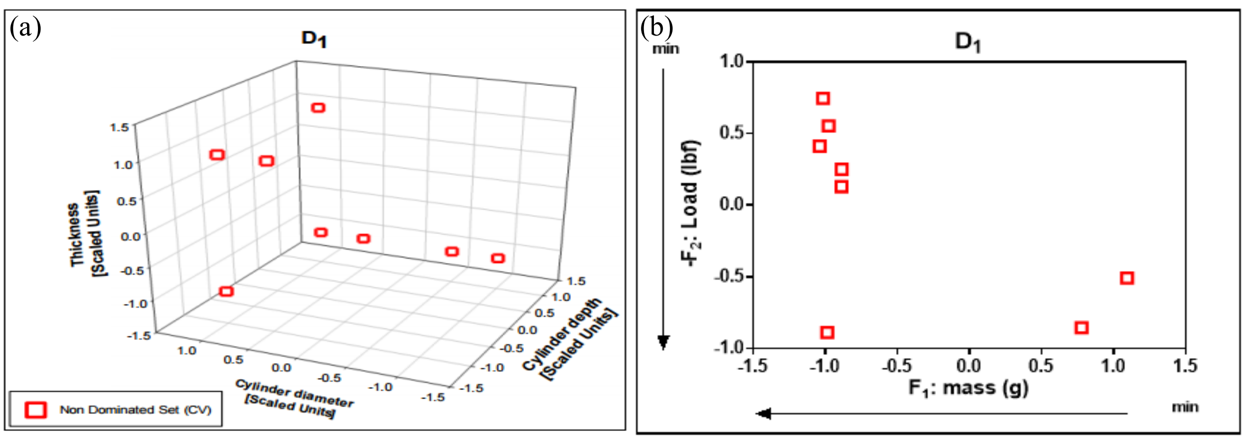

Figure 9: Set of simulated points that are potentially efficient (D_1), (a) controllable variables and (b) performance measures.

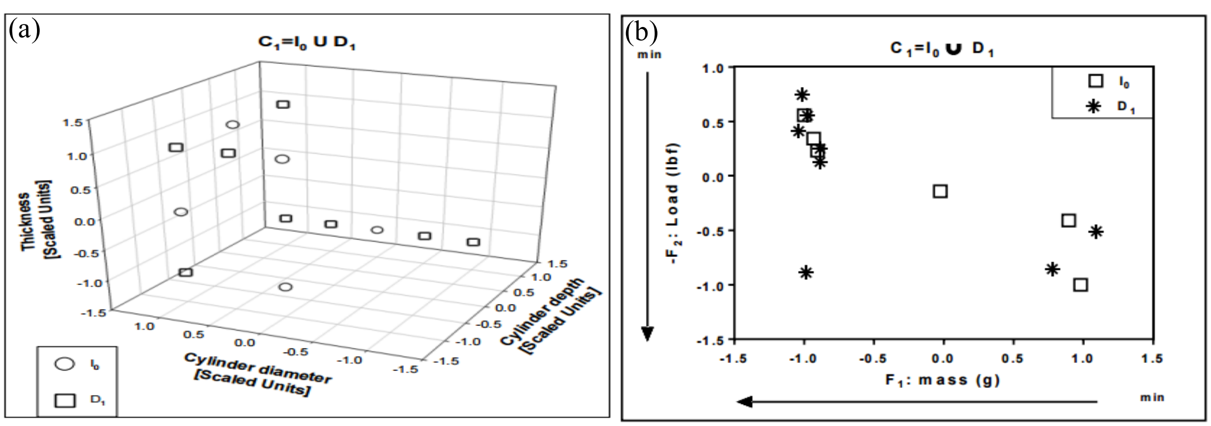

Figure 10: Initial Pairwise comparison $I_0 \cup D_1$ (a) controllable variables and (b) performance measures.

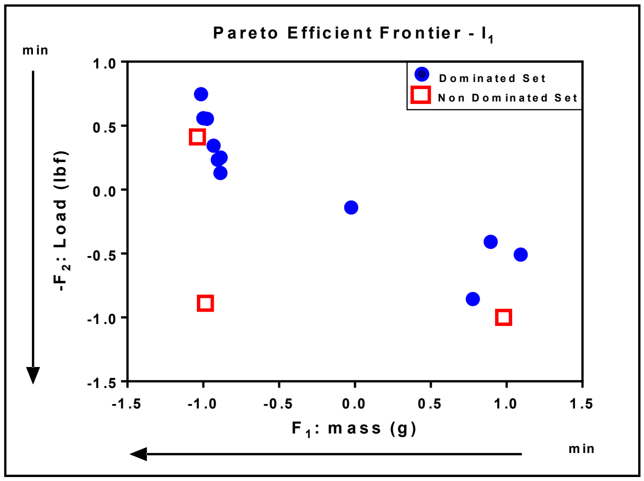

Figure 11: Pairwise comparison for the incumbent solution (I_1).

Termination: When the comparison was performed, no more points were added to the efficient frontier. Given that no other point was added to the efficient frontier, the three identified solutions by the method represent the best possible trade-offs between mass and strength as shown in Figure 12. The details of the final solution are described in Table 2.

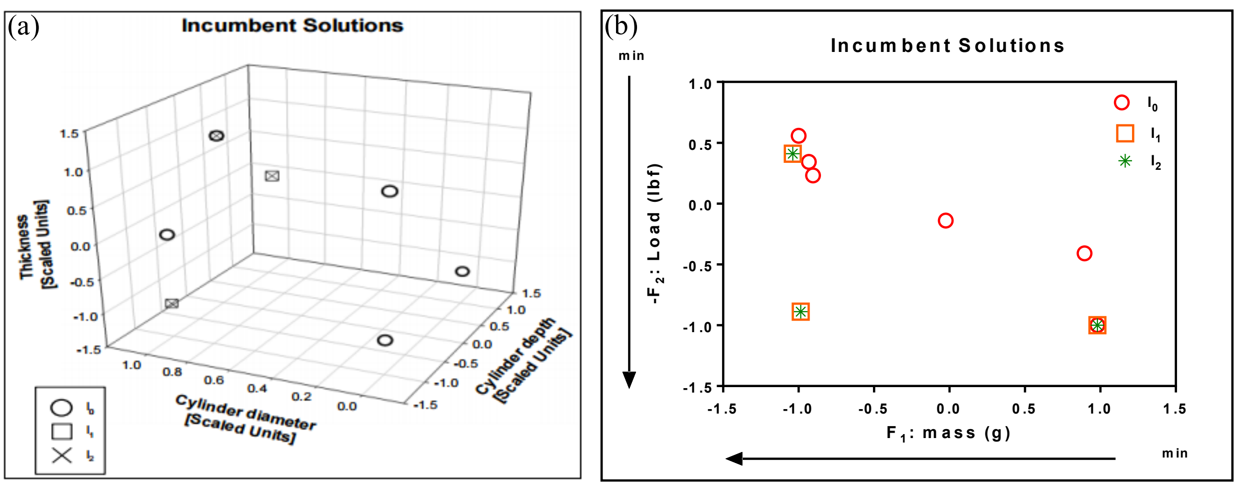

Figure 12: Each of the incumbent frontiers (I_0-I_1-I_2) of the problem under study, (a) controllable variables and (b) performance measures.

Table 2: Pareto-efficient frontier.

	Pareto-efficient frontier					
Assembly ID	**Position**	**Thickness(in)**	**Cylinder diameter (in)**	**Cylinder depth (in)**	**mass (g)**	**Max Load (lbf)**
1	105	0.092	0.041	0.230	11.2716	139.597
2	115	0.230	0.041	0.230	11.0938	44.333
5	12	0.161	0.041	0.460	17.8560	147.733

The tradeoffs in mass and flexural strength in the Pareto-efficient solutions can be appreciated in Table 2 and Figure 12. A total of 24 assemblies comprising 168 parts were necessary to carry out this case study. The method stopped automatically in two iterations, requiring only the 3D printing of eight additional assemblies. From Figure 12, it is noticeable how a very competitive design configuration was uncovered by the application of the method. This solution would have not been found solely with the initial DOE.

CONCLUSIONS AND FUTURE WORK

This work presents a case study on the application of a multicriteria optimization method developed in a previous work for the design of an interlocking device. The aim of this work is to show the potential of the proposed method for a truly experimental endeavor. In its current state, the method is an improvement over single-pass methods as well as the use of Data Envelopment Analysis models as previously proposed by our research group. Manufacturing decisions regarding design, control and improvement of processes and systems can greatly benefit from using the proposed optimization strategy from the point of view of its capabilities -multicriteria, multifactorial- as well as its frugality in terms of the number of simulation runs.

Current efforts in our group include the devise of a recycling system for PET bottles that can result in parts, similar to the prototype presented in this manuscript, and that can be used to produce planar assemblies. The first planar assembly –still a 3D printed prototype- is a stepping stone, as shown in Figure 13. A PET bottle can result in up to eight parts that can be put together to add to such assembly. Preliminary tests indicate that the assembly can withstand a force of 250 lbs without losing integrity. The devise of such system will require frequent use of simulation and prototyping and, thus, multicriteria optimization as advocated in our work.

Figure 13. A 3D printed prototype for a stepping stone (Provided by S. Villanueva-Pérez et al.)

ACKNOWLEDGMENTS

The authors want to thank to Boris Renteria for his aid in the use of the testing equipment in the General Engineering Department, UPRM. Figure 13 was kindly provided by Stephanie Villanueva-Pérez, Rafael López, Viviana Vázquez, Nestor Jorge, and Valerie Odeh This work was partially supported by USDA-NIFA Award 2015-38422-24064 sub award 1000000920 BE AWARE Project.

REFERENCES

Ancau, M., and C. Caizar. 2014. "The effectiveness of multi-criteria optimization in rapid prototyping." In *Proceedings of The Romanian Academy Series A-Mathematics Physics Technical* 15: 362-370.

Asadi-Eydivand, M., M. Solati-Hashjin, A. Fathi, M. Padashi, and N. A. Abu Osman. 2016a. "Optimal design of a 3D-printed scaffold using intelligent evolutionary algorithms." *Applied Soft Computing* 39:36-47.

Asadi-Eydivand, M., M. Solati-Hashjin, A. Fathi, M. Padashi, and N. A. Abu Osman. 2016b. "Effect of technical parameters on porous structure and strength of 3D printed calcium sulfate prototypes." *Robotics and Computer Integrated Manufacturing* 37:57-67.

Cabrera-Ríos, M., J. M. Castro, and C. A. Mount-Campbell. 2002. "Multiple Quality Criteria Optimization in In-Mold Coating (IMC) with a Data Envelopment Analysis Approach." Journal of Polymer Engineering 22:305-340.

Cabrera-Ríos, M., J. M. Castro, and C. A. Mount-Campbell. 2004. "Multiple Quality Criteria Optimization in Reactive In-Mold Coating with a Data Envelopment Analysis Approach II: A Case with More than Three Performance Measures." Journal of Polymer Engineering 24:435- 450.

Castro, C. E., M. Cabrera-Ríos, B. Lilly, J. M. Castro, and C. A. Mount-Campbell. 2003. "Identifying the Best Compromises Between Multiple Performance Measures in Injection Molding (IM) Using Data Envelopment Analysis (DEA)." Journal of Integrated Design & Process Science 7:77-87.

Castro, J. M., M. Cabrera-Ríos, and C. A. Mount-Campbell. 2004. "Modelling and Simulation in Reactive Polymer Processing." Modelling and Simulation in Materials Science and Engineering 12:S121-S149.

Castro, C. E., M. Cabrera-Ríos, B. Lilly, and J. M. Castro. 2005. "Simultaneous Optimization of Mold Design and Processing Conditions in Injection Molding." Journal of Polymer Engineering 25:459-486.

Camacho-Cáceres, K. I., J. C. Acevedo-Díaz, M. Ortiz-Mojer, L. M. Pérez-Marty, J. Irizarry, M. Cabrera-Ríos, and C. E. Isaza. 2015. "Multiple Criteria Optimization Joint Analyses of Microarray Experiments in Lung Cancer: From Existing Microarray Data to New Knowledge." *Cancer Medicine* 4:1884-1900.

Clark, A. J., W. Jianxun, T. Xiaobo, and P. K. Mckinley. 2014. "Balancing performance and efficiency in a robotic fish with evolutionary multiobjective optimization." *Evolvable Systems (ICES) 2014 IEEE International Conference* 227-234.

Irisarri, F. -X., F. Laurin, F. -H. Leroy, and J. -F. Maire. 2011. "Computational strategy for multiobjective optimization of composite stiffened panels." *Composite Structures* 93:1158-1167.

Gibson, I., D. Rosen, and B. Stucker. 2015. *Additive manufacturing technologies: 3D printing, rapid prototyping and direct digital manufacturing*. 2nd ed. London: Springer.

Lu, B., D. Li, and X. Tian. 2015. "Development trends in additive manufacturing and 3D printing." *Engineering* 1:085-089.

Marinić-Kragić, I., D. Vučina, and Z. Milas. 2016. "3D shape optimization of fan vanes for multiple operating regimes subject to efficiency and noise-related excellence criteria and constraints." *Engineering Applications of Computational Fluid Mechanics* 10:209-227.

Marler, R., and J. Arora. 2004. "Survey of multi-objective optimization methods for engineering." *Structural and Multidisciplinary Optimization* 26:369-395.

Mearian, L. 2014. "3D printers churn out Ford prototypes." *Computerworld* 48:41.

Micallef, J. 2015. *Beginning design for 3D printing*. Berkeley, CA: A press.

Niño-Pérez, E., Y. M. Méndez-Vázquez, D. E. Arias-González, and M. Cabrera-Ríos. 2017. "A Simulation-Optimization Strategy to Deal Simultaneously with Tens of Decision Variables and Multiple Performance Measures in Manufacturing." *Journal of Simulation* 2017:1-13.

Olivier Gonzalez, D. S., S. Borros Gomez, and G. Reyes Pozo. 2010. "New method for optimized design of new materials systems intended to be applied at additive manufacturing techniques." *Annals of DAAAM & Proceedings*, 1545-1546.

Peacock, S. R. 2014. "Why manufacturing matters: 3D printing, computer-aided designs, and the rise of end-user patent infringement." *William and Mary Law Review* 55:1933-1960.

Pohlak, M., J. Majak, K. Karjust, and R. Küttner. 2010. "Multi-criteria optimization of large composite parts." *Composite Structures* 92:2146-2152.

Ransikarbum, K., S. Ha, J. Ma, and N. Kim. 2017. "Multi-objective optimization analysis for part-to-Printer assignment in a network of 3D fused deposition modeling." *Journal of Manufacturing Systems* 43:35-46.

Rayna, T., and L. Striukova. 2016. "From rapid prototyping to home fabrication: How 3D printing is changing business model innovation." *Technological Forecasting & Social Change* 102:214-224.

Rodríguez-Yañez, B., Y. M. Méndez-Vázquez, and M. Cabrera-Ríos. 2014. "Simulation-based Process Windows Simultaneously Considering Two and Three Conflicting Criteria in Injection Molding." Production & Manufacturing Research: An Open Access Journal 2:603-623.

Schatz, M. E., E. Hermanutz, and H. J. Baier. 2017. "Multi-criteria optimization of an aircraft propeller considering manufacturing." *Structural and Multidisciplinary Optimization* 55:899-911.

Stankovic, T., J. Mueller, P. Egan, and K. Shea. 2015. "A Generalized Optimality Criteria Method for Optimization of Additively Manufactured Multimaterial Lattice Structures." *Journal of Mechanical Design* 137:111705/1-111705/12.

AUTHOR BIOGRAPHIES

ESMERALDA NIÑO-PÉREZ obtained a MS degree in Industrial Engineering from the University of Puerto Rico at Mayagüez. She was a graduate research assistant at the Applied Optimization Group at UPRM. Currently, she is an engineer at the building technology company Zero Damage LLC. Her research interests relate to manufacturing, simulation-optimization and artificial intelligence Her email is enino@zerodam.com.

CÉSAR A. RIVERA-COLLAZO obtained a BS degree in Mechanical Engineering from the University of Puerto Rico at Mayagüez. At the time, he was research assistant at the Applied Optimization Group at UPRM. His research interests relate to manufacturing and optimization. He is currently a Structural Design Engineer at the Boeing Company. His email is cesar.rivera100@gmail.com

YAILEEEN M. MÉNDEZ-VÁZQUEZ obtained a BS and MS degree in Industrial Engineering from the University of Puerto Rico at Mayagüez. Currently, she is Ph.D. student of Industrial Engineering at Oregon State University. She is a graduate research assistant at the Human Analytics Lab. Her research interests include experimental design, simulation-optimization and the application of human learning simulation to workforce planning. Her email is mendezvy@oregonstate.edu.

MAURICIO CABRERA-RÍOS obtained M.S. and Ph.D. degrees in Industrial and Systems Engineering from The Ohio State University. He is a Professor in the Industrial Engineering Department at University of Puerto Rico – Mayagüez. His research interests include manufacturing optimization and biological data analysis. His email is mauricio.cabrera1@upr.edu. His research group's email is Applied.optimization@gmail.com.