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Design Optimization with Genetic Algorithms and Surrogate Models for Lightening Parts Made by Additive Manufacturing

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Summary

Additive manufacturing (AM) has become in a competitive method for short production and high flexibility applications. Few constraints in the manufacturing process involve a great design freedom, allowing weight minimization by internal cellular and lattice structures and keeping the minimal mechanical requirements.

An optimization method based on genetic algorithms (GAs) and CAD/FEM simulations is proposed to optimize the cellular structure design and minimize the weight for AM parts. New optimization strategies based on GA and surrogate models are evaluated and compared to reduce as far as possible the number of simulations by FEM.

Keywords: *additive manufacturing, weight minimization, genetic algorithms, surrogate models, finite element method, linear interpolation based on Delaunay triangulation, feasible/unfeasible border.*

1. Introduction and objectives

The use of AM technologies and CAD-MEF allows minimizing part weight by cellular structures repeated without changing the previous external design. Results obtained in the FEM simulations allow knowing the mechanical behaviour, enabling the evaluation of the fitness function and applying GAs in the optimal searching.

AM technologies are very competitive especially in applications where short-medium production series and high flexibility are required. Weight minimization not only means a greater efficiency in multiple applications, but also significant reduction of manufacturing costs, either material savings or manufacturing time.

However, as it relates to short production, the accuracy in the optimal design searching has no a significant impact in the cost per unit as occurs in large production cases. Hence, in AM applications does not make sense employing an excessive time in the design optimization if the achieved manufacturing cost reduction is not as valuable as the extra cost related to design.

For these reasons, weight minimization will be made through repeated cell geometries (from a pattern) inside the part, which implies less variability of individuals and a smaller number of design variables (less than 7), but greatly facilitates CAD and optimization tasks, reducing the design costs significantly.

On the other hand, evaluation of the fitness function of each one of the individual generated during the GA evolution requires FEM simulations. This would involve an excessive computational time[1]. Hence, it is approached the use of surrogate models to estimate the FEM results without doing the simulations and then reducing the number of the computationally expensive analysis as much as possible[2].

until at least "n" points (n=number of design variables) have been added in this phase. After that, the MAPE of the last added point (response estimations compared to simulations) is evaluated. If the MAPE is bigger than 1%, then the metamodel is uploaded with this last point and this GA is executed again. And so on until the MAPE value is lower than 1%.

Subsequently a final GA (configuration 6 with 200 generations) is run, using LIDT to calculate the fitness function value. The best individual is simulated by FEM. If it is in the feasible zone, it will be the optimum, otherwise the will be added to the data and the metamodel will be uploaded to execute again this final GA. And so on until reaching a feasible optimum.

In 10 different runs of the reference problem, the optimal fitness function average was F=1603.715, very close to the fitness value of the theoretical optimum (1600.809), with an average of 62 evaluated designs. A case study with FEM simulations (see Figure 3) in which it is pretended to minimize the weight of a blade for wind power micro-turbine lightened by cellular structures (3 design variables) keeping the maximum deflection under 15mm (constraint) was also solved.

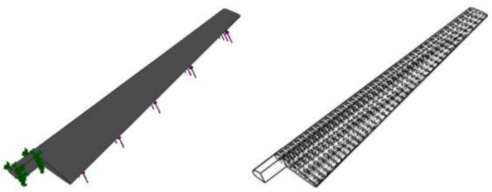

Figure 3. Case study geometry

The optimal value obtained after 40 FEM simulations has a mass of 1632.55g. This same problem was also solved by an optimization method based on Box-Behnken DOE and optimal estimation by response surface method (BBRS), an optimization strategy available in the commercial software of design and FEM simulations, SolidWorks. This method achieves an optimal of 1690.07g with only 14 simulations. The proposed methodology reaches an optimum 3.52% better but requires quite more simulations.

5.3. Version 3

The last 2 phases of the program (based on GAs) were tested by excluding different data set in order to evaluate the convergence of the program to the optimum. The conclusions obtained in this analysis are listed below:

-The points added in the internal border approximation do not influence in the quality of the optimum, so that this step was excluded.

-The phase of border approximation along the edges is done only edge by edge, getting a deviation from the real border line lower than 1% at each affected edge. This helps to select correctly the best corner of the feasible/unfeasible border for the next phase of the code.

-The addition of new middle points between the best border corner and the remaining adjacent corners involves incorporating a lot of points. It was observed that only combining the best border corner with the "n-1" best remaining adjacent corners the method also converges to the theoretical optimum.

Version 3 was run 10 times with the reference problem, obtaining as optimal fitness function average F=1606.0.50, with an average of 44 sampling points. The new version converges to a solution 0.15% worse than the previous version, but requires only 44 instead of 62 simulations, reducing in approx. 29% the CPU time. With the previous case study (with FEM analysis), an optimal design of 1634.85g and only 29 sampling points was found. This optimal design has incremented the mass a 0.14% versus the optimal of version 2, but the number of evaluated designs was reduced from 40 to 29 (approx. 27.5% of CPU time reduction). Compared with the result of BBRS method, this program improves the optimal 3.38% but requires more sampling points (29 versus 14). However, it ensures the convergence to the theoretical optimum due to the refinement loops, while the BBRS method does not guarantee the convergence to a feasible design and his refinement is quite limited by the equation shape to be fitted. In addition, it should be noted that the sampling point number 18 (added during the border approximation along the edges) improves the optimum obtained by BBRS method with only 4 more simulations.

6. Conclusions

A new optimization method for cellular structures in AM has been presented, based on a 2-level full factorial DOE and central point, border approximation along the edges, addition of new middle points between the best border corner and the best "n-1" adjacent remaining corners, addition of new points along the border using GAs (proximity penalty and LIDT) and a final optimal searching through a GA (with LIDT).

The border approximation phase along the edges allows getting good designs with a low sampling (in many cases the optimum is in the domain boundary). The proximity penalty in the GA allows adding new points along the feasible/unfeasible border, exploring these interesting zones. The linear interpolation metamodel reduces the FEM simulations drastically, obtaining a methodology which guarantees the convergence to the optimal design with a low sampling density.

7. References

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