Proceedings Paper:

Buchanan Berumen, Edgar orcid.org/0000-0001-6587-8808, Dubey, Rahul orcid.org/0000-0003-1524-7797, Hickinbotham, Simon John orcid.org/0000-0003-0880-4460 et al. (4 more authors) (Accepted: 2023) Investigation of starting conditions in generative processes for the design of engineering structures. In: 2023 IEEE Symposium Series on Computational Intelligence:International Conference on Evolvable Systems (ICES). 2023 IEEE Symposium Series on Computational Intelligence, 05-08 Dec 2023 , MEX. (In Press)

Investigation of starting conditions in generative processes for the design of engineering structures

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***Abstract*—Engineering design has traditionally involved human engineers manually creating and iterating on designs based on their expertise and knowledge. Bio-inspired Evolutionary Development (EvoDevo) generative algorithms aim to explore a much larger design space that may not have ever been considered by human engineers. However, for complex systems, the designer is often required to start the EvoDevo process with an initial design solution (seed) which the development process will optimize. The question is will a relatively good starting seed always yield a good set of design solutions. This paper considers this question and suggests that sub-optimal seeds can provide, up to certain limits, better design solutions than relatively more optimal seeds. In addition, this paper highlights the importance of designing the appropriate seed for the appropriate problem. In this paper, the problem analysed is the structural performance of a Warren Truss (bridge-like structure) under a single load. The main conclusion of this paper is that up to a limit sub-optimal seeds provide in general better sets of solutions than more optimal seeds. After this limit, the performance of sub-optimal seed starts to degrade as parts of the phenotype landscape become inaccessible.**

***Index Terms*—evodevo, generative design, structural engineering, genetic algorithms, neural networks**

I. Introduction

It is a common practice that an experienced engineer provides the design of engineering solutions for any given problem, often starting from a previously well-formed design [1]. However, in recent years novel tools have been created to enhance the design process assisted by computational intelligence techniques. Most of the early work consisted of one-to-one mapping, direct encoding, of the solution where changes were made directly in the solution [2]. While proving successful this process proved to be slow and computationally expensive in order to find the optimal solution in the fitness landscape, and a question of scalability is raised. Generative design [3] has been used, mainly for theoretical studies and seldom for real engineering structures, alongside evolutionary techniques to reduce time and make fitness landscape exploration more efficient [4], [5].

Recent work has updated evolutionary (*Evo*) techniques with a developmental component (*Devo*) inspired by the evolutionary development (*EvoDevo*) in biology [6] where the *EvoDevo* evolves the development rules, an overview can be found in [7]. Some examples of *EvoDevo* used to evolve design can be found in [8]–[10]. Price et al [11] have demonstrated the use of *Devo* processes to create a bracket component. Recent work shown in [12] demonstrated the use of *EvoDevo* to optimize the structure of the Warren truss problem (bridge-like structure). In this approach, an artificial gene regulatory network (GRN) regulates the growth from an initial structure (seed) to the final solution during the *Devo* process. The fitness score is taken at the last *Devo* step by the *Evo* process and the GRN is optimized with this information. One of the main motivations of *EvoDevo* is that the evolved GRNs can provide efficient solutions when subjected to different conditions.

In contrast to traditional evolutionary processes (where random initial starting points are often chosen), in the *EvoDevo* process a seed is required to start the process. The concept of a seed, introduced in [12], is defined as an initial solution (structure) whose main requirement is to connect the supports and the external load. In previous work, the seed provided to the *EvoDevo* process is hand-designed and its quality is relatively good [12] where quality in this context refers to the behaviour of a structure of having a subjective low volume and low strain energy. This approach of hand-designing the seed works with the assumption that the designer has the knowledge of what a good quality initial design (seed) looks like. This paper argues that the shape of the seed can have a significant impact on the quality of the solutions found by an *EvoDevo* process. In this paper, the quality of the set solutions found at the end of an *EvoDevo* process is analysed for four different initial seeds each with a different degree of quality (as judged by an engineer). This is done with the objective of testing the following two hypotheses.

1) The relative position of the seed in the fitness landscape has no significant impact on the location of the Pareto front and the quality of the solutions found.
2) The design of the seed has no impact on the structure landscape limiting the space *EvoDevo* can explore with.

This paper shows that the designer needs to carefully select the appropriate seed for an *EvoDevo* process in order to find the best engineering designs for a given problem. This is

This work was funded by EPSRC, UK, grant reference EP/V007335/1.

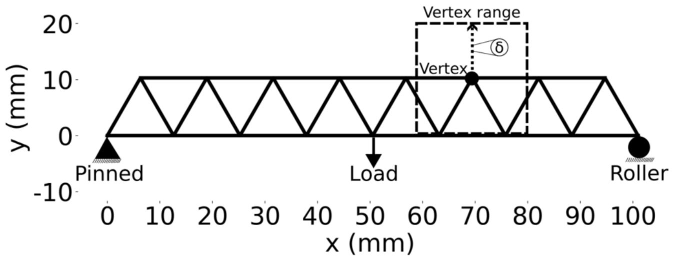


Fig. 1. Loading on a fifteen-segment truss. For all the experiments all the structures are pinned in the vertex at the left-hand side, roller in the vertex at the right-hand side and the load is located at the fixed vertex in the middle. The position of each movable vertex is regulated by the "output deltas" (δ). At each *Devo* step a vertex can be moved up to 1 mm at any x and y direction. In a single *Devo* process a vertex can move up to 10 mm in a direction as shown in the vertex range.

achieved by demonstrating the counterintuitive effect that a relatively sub-optimal seed can find better sets of solutions than a more optimal initial seed. Therefore, a set of diverse seeds might need to be algorithmically produced in order to identify the most suitable seed. The key contribution of this paper is the first study of the impact of the seed/initial structure on the quality of solutions found in the *EvoDevo* process for an engineering problem (in this case a Warren Truss). This study is carried out on the structural (phenotype) and fitness (behaviour) landscapes.

II. Experimental methodology

The Evolutionary Developmental (*EvoDevo*) approach used in this paper is similar to that introduced in [12]. An evolutionary algorithm (EA) is used to evolve populations of Gene Regulatory Networks (GRN). Each GRN leads the developmental process from a starting structure (seed) by changing the locations of the vertices in the structure at each step during the developmental process (*Devo*). Lastly, the EA takes the fitness from the last *Devo* step as the score to generate the new population.

The *Devo* process in Hickinbotham [12] takes place in a fixed set of steps (in this case 10), although it is recognised that this is an arbitrary, and potentially limiting choice. At each step, the locations of the vertices are changed by the GRN which in this work is implemented by a feedforward neural network. The amount of change is regulated by "output deltas" (δ) of the neural network. It is important to highlight that a single vertex can move up to 1 mm at each *Devo* step in each x and y direction, therefore a vertex can move up to 10 mm in any direction at each development step as illustrated in figure 1. For all the experiments, all the structures have a pinned support on the vertex at the left-hand side, roller support on the vertex at the right-hand side and the load is located at the vertex in the middle, which is constrained from moving.

This paper studies the influence of the seed in two solution representations (phenotype and behavioural). The first representation, *phenotype*, is at the structure level, a set of vertices, at the last developmental step. The second representation, *behavioural*, is the multi-objective fitness score of the organism when subjected to an external load.

Four different seeds are analysed in this paper and shown in figure 2: *seed 1*, *seed 2*, *seed 3* and *seed 4*. *Seed 1* was manually designed. *Seed 2*, *seed 3* and *seed 4* were sub-optimal solutions taken from evolved structures in an experiment using *seed 1*. These last three seeds were chosen because of their different phenotype features and positions in the behavioural landscape. Vertices for *seed 2* are skewed in the positive y-direction. Vertices for *seed 3* are skewed towards the negative y-direction. Vertices for *seed 4* are even more skewed in the negative y-direction than the previous seed. *Seed 4* exhibits the worst quality in the behavioural landscape and *seed 1* exhibits the best quality.

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) [13] algorithm is used in this paper in combination with the Neuro-Evolution of Augmenting Topologies (NEAT) [14] algorithm to evolve the weights, biases and topologies of initial fully connected neural networks with no hidden nodes representing the GRNs. The optimal solutions are taken from the set Pareto front solutions from the last generation. The parameters used for the experiments in this paper can be found in table I.

The two objectives to minimize for the *Evo* process are volume and deflection that act as proxies for weight and stiffness (e.g. bridge with the least material but still safe). The volume of a single solution is defined as the sum of the volume of each member m in the solution M and is calculated using:

$$V = \sum_{m \in M} A_m L_m \tag{1}$$

where A_m is the cross-sectional area of m and L_m is the length of m. Deflection is defined as the maximum distance, deflection, travelled of a vertex d in the solution as shown in equation 2. The deflection is estimated using Finite Element Analysis (FEA) software.

$$D = max[d_0, ..., d_n] \tag{2}$$

The Mann-Whitney U test [15] is used here to test the hypothesis that all the samples from two groups are not independent of each other. For this, a three-star ranking system is used where one star (*) represents $p < 0.05$, two stars (**) represent $p < 0.01$, and *** represents $p < 0.001$ and p is the probability.

The Pareto-agnostic hypervolume (HV) metric [16] is used to measure the quality of the Pareto fronts. High values of HV represent better Pareto fronts. Also, the HV requires a point of reference and for this, the coordinate for *seed 4* is used.

III. Results

The results shown present the quality of solutions at the end of the *EvoDevo* process. The analysis is carried out by assessing the multi-objective fitness scores produced by

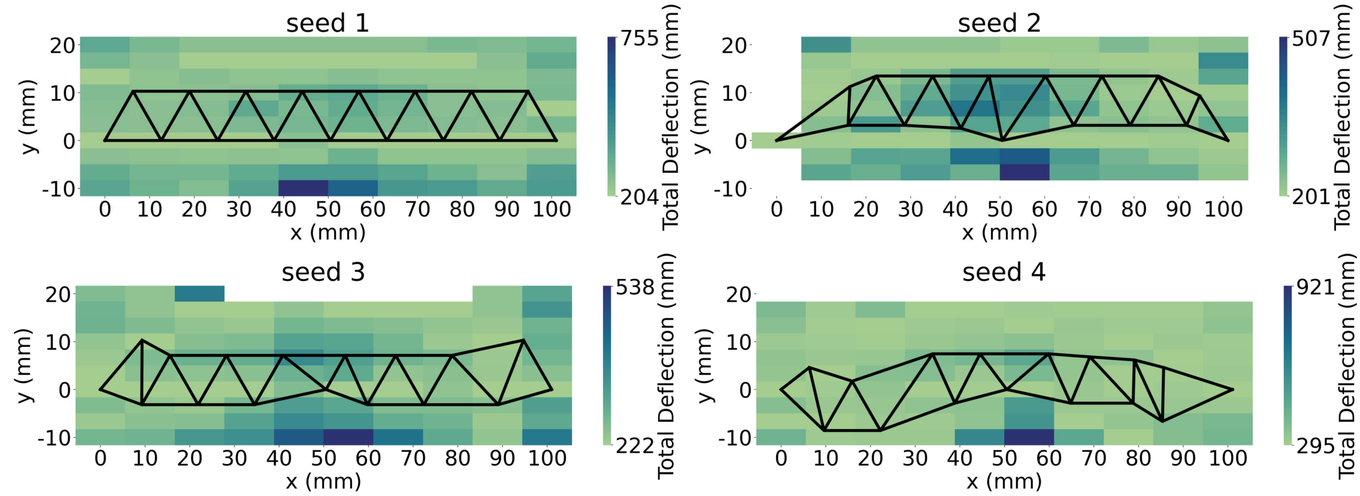


Fig. 2. Seeds used for the experiments shown in this paper. *Seed 1* was manually constructed, *seed 2*, *3* and *4* were taken from an EvoDevo experiment. The heat maps represent the lowest deflection across all generations and all replicates found when a vertex was placed in that coordinate. The landscape is not entirely covered for *seed 2*, *3* and *4* as indicated with the white cells.

TABLE I
THESE PARAMETERS ARE USED FOR EACH SEED IN THIS PAPER.

Parameter	Value
Number of replicates	20
Population	50
Generations	200
Developmental steps	10
Max δ	1 mm

each seed and by showing some examples of the generated structures.

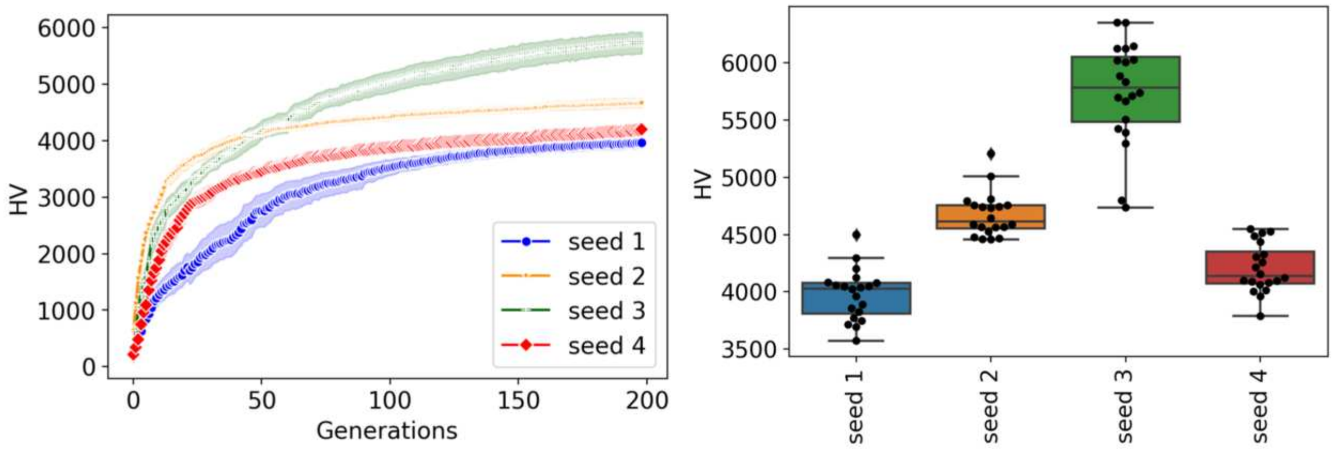
The structure of the seed can influence the lowest deflection found at each coordinate by the *EvoDevo* process. The heatmaps in figure 2 represent the lowest deflection achieved at each coordinate in the phenotype landscape across all the replicates (repetitions) and generations. Overall, *seed 2* and *seed 3* are able to find lower values of deflection than *seed 1* and *seed 4* as shown in the scales in the colour bars. Also, vertices located in the negative y direction experience the highest values of deflection as highlighted in the darker regions of the heatmaps.

The locations of the vertices in the seed can set hard boundaries in the phenotype landscape limiting the optimal solution reachability. White cells represent solutions that were not found in any replicate in any generation at that coordinate as shown in figure 2. In contrast to *seed 1* where the entire landscape is covered by *EvoDevo*, the landscape for *seed 2*, *3* and *4* is not entirely covered as shown with the white cells. This occurs for two reasons. First, the number of *Devo* steps is not enough to move a vertex to that location of the phenotype space. Second, the value for δ is too small (1 mm). The white cells are more than 10 mm apart from the closest vertex. For example, the vertices for *seed 2* are skewed towards the top-right corner and *EvoDevo* is unable to reach the region in the bottom-left corner. A similar case for *seed 3* and *4* is that vertices are skewed towards the bottom and *EvoDevo* is unable to reach the top part of the landscape.

The issue of hard boundaries in the phenotype landscape can be addressed in two ways each with a trade-off. In the first approach, the number of *Devo* steps can be increased, however, this increases the number of evaluations hence the computation time of the *EvoDevo* process. In the second approach, the δ value can be increased, however, the exploration of the landscape will increase and with this the time that it takes to find the global optimum.

The HV scores of the Pareto fronts produced by *seed 3* are significantly higher than the other three seeds. Figure 3a shows the convergence of the HV values at each generation at each replicate. Even though *seed 2* is initially faster at finding higher HV values, *seed 3* finds the best Pareto fronts across the three seeds after 50 generations. Figure 3b shows the boxplots of the last generation where *seed 3* is *** different than the other three seeds. In other words, *seed 3* experiences higher values of HV and with this better quality of Pareto. This result rejects *hypothesis 1* and validates the statement that the position of the seed in the fitness landscape has a significant impact on the resulting Pareto fronts. More details about the Pareto fronts are described next.

For the experiments shown in this paper, the farther the seed is from the origin, the closer the Pareto front is to the origin as shown in the behavioural landscape in figure 4 with the exception of *seed 4* which will be addressed later. Even though *seed 1* is closer to the origin than the other two starting seeds, this seed finds the least optimal set of solutions. There are three possible reasons for this behaviour in the *EvoDevo* process: 1) It can be possible that the structure for *seed 1* is located at a local optimum and the *EvoDevo* algorithm is unable to escape this region. 2) *seed 2* and *seed 3* are located in a richer space in terms of the diversity of structure solutions. 3) The ranking nature of NSGA-II incorporates a crowding



(a) (b)

Fig. 3. Convergence of the hypervolume at each generation for all the replicates (a) and box plots at the last generation (b). *Seed 3* is *** different than the other three seeds.

distance measure, that pushes the solutions to extend the arms of the Pareto front instead of pushing the solutions towards [0,0] in the fitness landscape. Point 3) can also be visualized in Figure 4a where the Pareto front arms are shorter for *seed 3* than the other two seeds where the volume is lower than 425 and the deflection is lower than 700.

The main reason why *seed 4* has worse performance than *seed 3* is that its vertices are located in a region which makes it very difficult for the *EvoDevo* process to move them to the optimal region. Many of the vertices for *seed 4* are close to the boundary at the negative y-direction, therefore the upper region of the phenotype landscape becomes unreachable as the distance is more than 10 mm away from the closest vertex as shown in figure 2. This could probably be improved by increasing the delta step as mentioned before. This result might reject *hypothesis 2* suggesting that the design of the seed has an impact on the final structure and its position in the landscape. This impact is shown as an unreachable region during the *Devo* process that changes from seed to seed. The region with optimal solutions is described next.

The colour of the cells in figure 5 represents the number of solutions found at that coordinate at the last generation across all the replicates for *seed 3*. From the heat map and figure 5d, it can be visualized that many of the vertices of structures at the last generation are concentrated at the row of positive 10 mm and at the row of 0 mm in the y-direction. The row at positive 10 mm in the y-direction is unreachable for a few vertices for *seed 4* and this demonstrates its poor performance relative to the other three seeds.

Even though the optimality of *seed 3* [391.32, 572.45] was inferior to *seed 1* [387.5, 451.39], the *EvoDevo* algorithm was able to find better solutions using *seed 3*. Three examples of solutions found at the knee region in the Pareto front (volume less than 380 and deflection less than 400) for *seed 3* are shown in Figures 5a, b and c. Of the three solutions (a) has the lowest volume with the highest deflection [371.20, 400.54], (c) has the highest volume with the lowest deflection [384.62, 351.94] and (b) is somewhere in the middle [375.54, 379.94]. The white lines represent the final solution and the black lines represent the *seed 3*. It is important to highlight that even though solutions in the knee region produced by *seed 3* resemble more *seed 1*, these solutions were not found by *seed 1*, suggesting that *seed 1* fails to escape the initial local optima solution.

In summary, the position of the seed in the fitness, behavioural, space can lead to better Pareto fronts, in this case, a lower quality of initial seed. However, it is important to note that careful choice is required as the location of the vertices at the seed can restrict the available search space at the structural, phenotype, representation as shown with *seed 4*. Therefore, careful design decision needs to be taken when creating the seed for an *EvoDevo* process.

IV. Conclusion

The Evolutionary Development (*EvoDevo*) algorithms used in generative design for engineering structures need a starting solution (seed) to develop. In previous work, a deliberately designed "good" quality seed was produced with the expectation that this seed would develop into the best solution the *EvoDevo* process could deliver. However, as shown in this paper, this is not guaranteed.

Four different seeds with different degrees of quality were used as starting conditions for the *EvoDevo* process. The results showed that a relatively low-quality seed can find better solutions than high-quality seeds. This concept applies as long as the *EvoDevo* process is able to move the vertices to the location with the highest quality of solutions.

The main two conclusions from this paper are the following: 1) Seed location in the fitness space has a correlation with the quality of the solutions found and the location of the Pareto front. 2) The seed can define hard boundaries in the structural landscape.

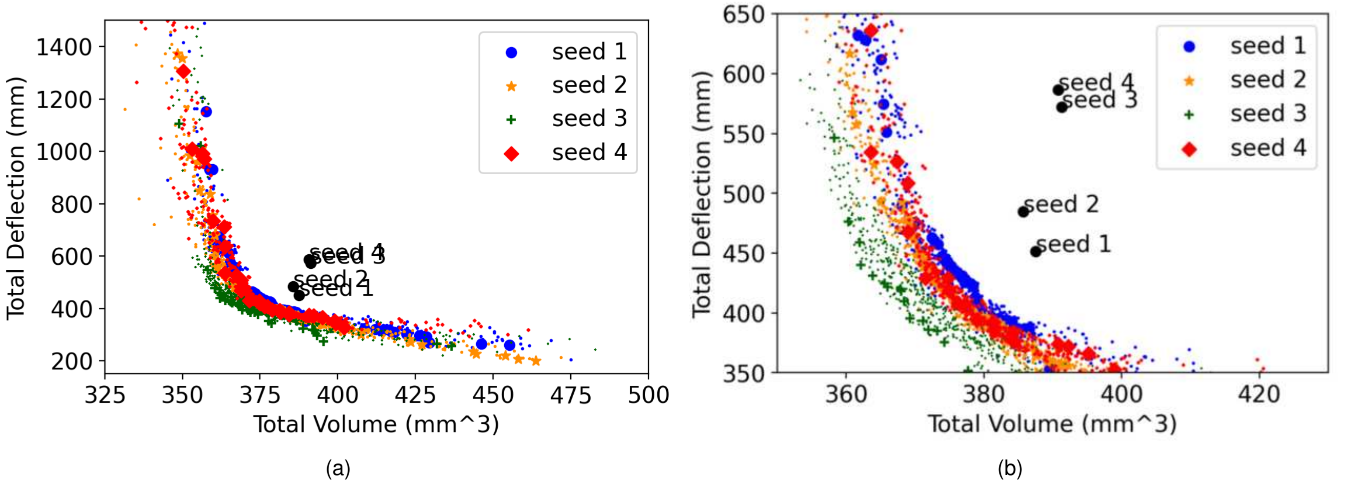


Fig. 4. All Pareto fronts aggregated from all the replicates for each seed as shown in (a) and (b) shows a close-up at the knee point. The Pareto front for *seed 3* is closest to the origin and the Pareto front for *seed 1* is the farthest. Even though the quality of *seed 4* is relatively the worst of all the seeds, the Pareto front is closer to the origin than *seed 1*. The Pareto arms for *seed 3* are shorter than the other three seeds.

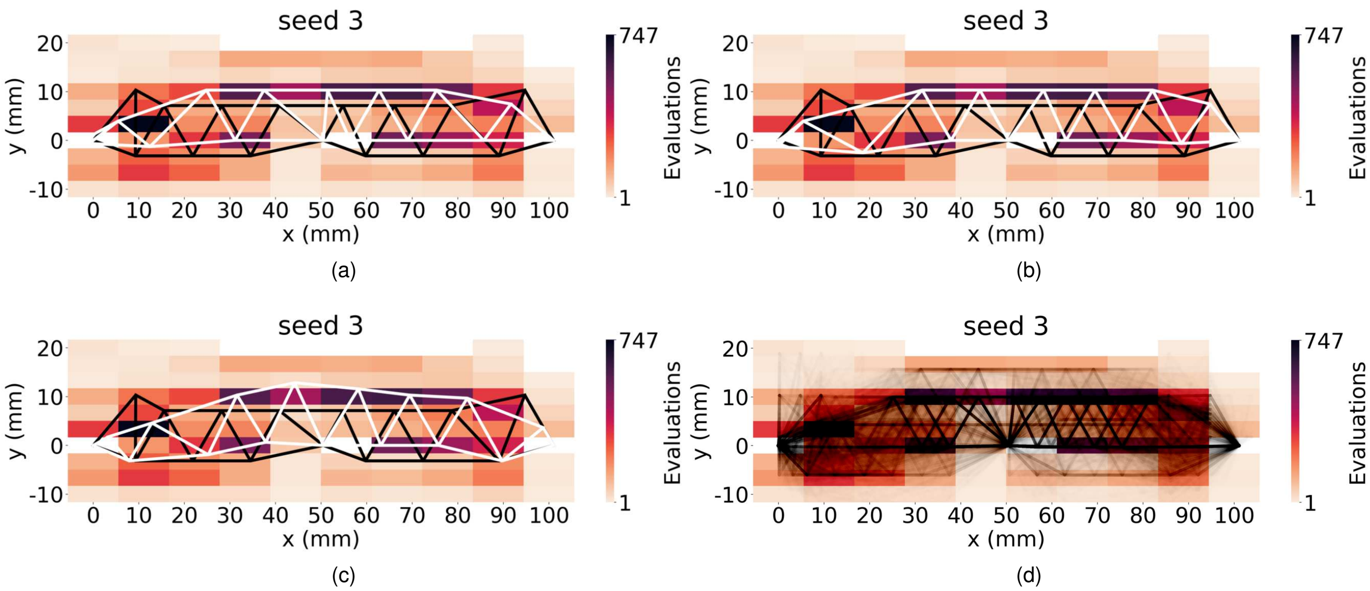


Fig. 5. Figures (a), (b) and (c) represent three examples of solutions (in white) found in the knee region at the Pareto front for *seed 3* (in black) each with a coordinate of [371.20, 400.54], [375.54, 379.94] and [384.62, 351.94] respectively where (a) has the lowest volume with the highest deflection and (c) has the highest volume with the lowest deflection. Figure (d) illustrates all the structures at the last generation for all the replicates. The colour of the cell represents the number of solutions found with a vertex at that coordinate at the generation.

In other words, this paper hypothesises that there is a trade-off in the location of a seed relative to the fitness landscape. A seed placed close to the origin can experience optimization problems due to the seed being located at local optima. Whereas, a seed located too far from the origin is unable to reach the global optimum due to the limitations in the exploration of the structure representation.

This result raises the question: how to design/create the best seed that produces the most optimal solutions for an *EvoDevo* process? Some possibilities are described next and future work will investigate and analyze each option in order to identify the best approach. In addition, further work will explore other design problems besides the Warren truss example.

1) An experienced qualified designer could deliberately design a lower-quality seed, with the assumption that this seed will yield better results. It is important that the designer is aware of the limitations of the algorithm including, and not only, the total distance a single vertex can be moved in the structure landscape.
2) A set of diverse seeds could be produced with quality diversity (QD) algorithms [17]. Each seed would be evaluated by the *EvoDevo* process and the seed providing

the best results will be chosen. This has the additional benefit that no prior knowledge is required to create the design of the seed with the trade-off that this might be computationally expensive.

3) A new multi-objective algorithm could be developed that influenced the fitness ranking to prioritise solutions in the 'knee' of the Pareto front.

Regardless of how the seed is designed, one of the requirements is that the GRN evolved should be flexible enough that when used with different seeds and different conditions the *Devo* process will provide feasible solutions.

Acknowledgement

This work was supported by EPSRC programme Grant Ref is EP/V007335/1, "RIED: Re-Imagining Engineering Design"[1]. The authors would like to acknowledge the Institute for Safe Autonomy (ISA)[2]. The authors thank Peter Kilpatrick for comments on an early draft of this manuscript.

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