Free-form Trap Design for Vibratory Feeders using a Genetic Algorithm and Dynamic Simulation

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Abstract: The task of feeding parts into a manufacturing system is still extensively handled using classical vibratory bowl feeders. However, the task of designing these feeders is complex and largely handled by experience and trial-and-error. This paper proposes a Self-Adaptive Genetic Algorithm based learning strategy that uses dynamic simulation to validate feeder designs. Compared to previous approaches of ensuring parts are oriented to a desired orientation by both deciding on a set of suitable mechanisms and then optimizing them to the specific part, this strategy learns a free-form design needing little prior domain knowledge from the designer. This novel approach to feeder design is validated on two different parts and it creates designs of hills and valley that reorients the parts to a single orientation. The found designs are validated both in simulation and with real-world experiments and achieve high success rates for reorienting the parts.

1 INTRODUCTION

Within the domain of assembly automation, the subparts of an assembly need to be physically available for the system. Whether assembly is done using a robot or a simpler type of manipulator, the parts need to be: 1) within reach, 2) singulated enough to be grasped, and 3) presented to the manipulator in a sufficiently accurate position and orientation for the assembly to be carried out successfully. This preparation task for the parts is typically referred to as *Part feeding*, and can often be the bottleneck which limits the performance of a manufacturing system. Therefore, efficient solutions are highly sought after. Although flexible feeder systems utilizing computer vision exist, the classical part feeding techniques of mechanically ensuring parts always are ready to be picked from a known position and orientation, are broadly applied in the manufacturing industry. In practice, this is often done using Vibratory Feeders (*VFs*), either as Vibratory Bowl Feeders (*VBF*s) or as Vibratory Linear Feeders (*VLF*s).

These vibratory feeders feed parts from bulk, using high-frequency micro-vibrations to convey parts along a helical track to a specific location at the outlet of the feeder from which the parts can then be further manipulated. While conveying, the parts encounter a series of passive mechanical orienting devices, called *traps*, consisting of geometric features such as: protrusions, narrowings of the track, and steps. The *VBF* is a popular approach e.g due to its robustness and simplicity under operation. However, a feeder is dedicated to a specific part, thus requiring new designs for new part types. Additionally, this design process is often associated with high complexity, which in total this leads to high costs due to the time a designer must spend on each design. The complexity especially comes from the process generally being driven by experience-based trial-and-error approaches, and thus addressing this issue with a method for facilitating the design will thereby reduce costs and enable deployment across a wider range of feeding tasks.

This paper addresses this problem by combining simulation-based evaluation, with a Self-Adaptive (Meyer-Nieberg and Beyer, 2007) Genetic Algorithm (GA) (Whitley, 1994), and in doing so it will be shown that the geometric features needed for orienting the parts can be learned. This is achieved by representing the feeder track, as a surface of connected vertices. The shape, and thereby the behavior of the feeder track, can be changed by manipulating the position of these vertices. The task is thus reduced to the problem of finding a vertex configuration which reliably aligns the parts. The resulting

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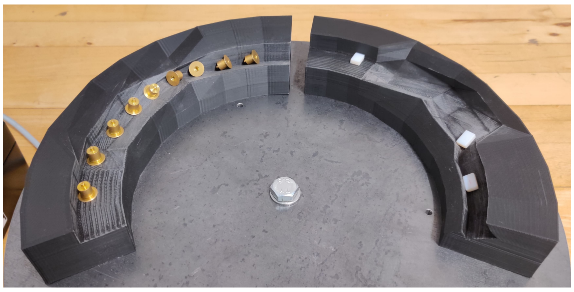


Figure 1: The two feeder tracks that was generated using the Free-Form Trap Designer presented in this paper along with their respective parts moving clockwise.

track surface then becomes a mixture of valleys and hills which redirects and reorient the part by taking advantage of its geometric features and mass distribution. Examples of two feeder designs generated with the approach presented in this paper can be seen in Figure 1. It should be noted that this approach does not rely on any existing trap design, but rather builds its own custom orienting features, and as a result provides a new method for generating reorienting traps requiring little to no domain specific knowledge from the designer.

The paper is structured as follows: Section 2 go through the related work. Section 3 provides an overview of the learning strategy as well as describing the tools used for the implementation. Next, Section 4 describes how the GA was adapted to the domain, followed by an elaboration on the self-adapting features of the GA in Section 5. Furthermore, Section 6 and Section 7 serves to evaluate and discuss the performance of the approach, respectively. Finally, the conclusion and proposed future work will be presented in Section 8 and 9, respectively.

2 RELATED WORK

Even though the design of vibratory part feeders are traditionally done more or less ad hoc, and that solutions are developed from the experience of the artisan making them, there have been attempts to formalize the process.

In this context, one must mention the extensive work of (Boothroyd, 2005). This work describes the mechanics of the *VF* and presents a system for classifying parts based on their geometric envelope together with a method to match these classifications to specific trap types. There are also guidelines and assistive functions for adjusting the parameters of a limited set of traps, but using them requires considerable domain knowledge and is not completely straight forward.

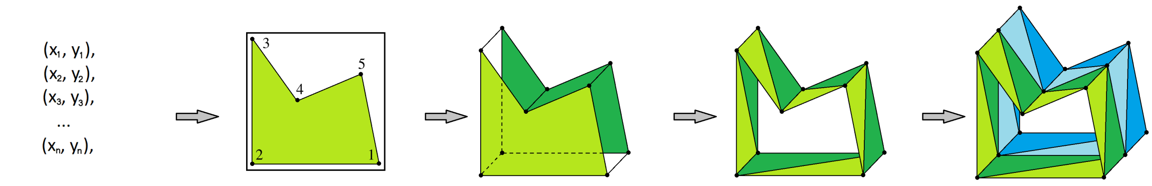
In order to approach a black box system for simpler trap design, which requires little human intervention or prior knowledge, simulation based approaches have been pursued in the past. This goes back to the work of (Berkowitz and Canny, 1996; Berkowitz and Canny, 1997), which modeled the feeding process with dynamic simulation and found good correspondence between the simulated results and real world experiments, however, not without some discrepancies.

In more recent work (Stocker and Reinhart, 2016), the authors investigate a trap type called a *Step*. The interaction between the step and a part is modeled through simulation, where they perform a sensitivity analysis for varying parameter settings of both trap and part geometry to map the behavior. This work illustrates that even simple traps with one parameter can have complex behavior, and that it would be beneficial to have automated optimization methods for the design problem.

Earlier work has pursued optimization methods to apply to generic trap principles. In (Hofmann et al., 2013) a *Random Search Algorithm* is presented. The algorithm is tested on a *Step* trap and optimizes this one parameter trap from a sample space of 13 discrete values for step height. However, it seems likely that the approach will struggle with multi-parameter traps (and thereby larger parameter spaces) and either will perform insufficient evaluation of the parameter space or require large amounts of samples.

Another approach to simulation-based optimization of traps can be found in (Mathiesen et al., 2018). This work presents an approach based in Bayesian Optimization with neighborhood approximation from Kernel Density Estimation. The approach works on simple data from the simulation with the evaluation providing a purely binomial outcome, i.e. did the trap perform as it should, resulting in a success, or did it fail. The approach is validated by attempting to orient a part with four different multi-parameter trap principles, these having 1-4 parameters, and with a parameter space of 19600 points for the trap having the largest solution space. Although this approach was able to solve the task within a feasible time frame, and being generically applicable to any trap principle, it still only works on specific traps with specific sets of associated parameters. Thus, a designer either has to choose which trap is useful for orienting the part in question, or try out all of them.

Another branch of approaches to trap design started with (Berretty et al., 1999) and was further extended in (Berretty et al., 2001). These works present dedicated algorithms to four specific trap principles, which find good values for their inherent design pa-



(a) 2D-points. (b) Cross-section. (c) Feeder segment. (d) Triangulation. (e) Surface.

Figure 2: Illustrates how a sequence of 2D-points and lengths gets translated in to its respective feeder design.

rameters under the assumption that parts move along a linear track, singulated, and at a constant velocity. The principle of the presented traps all relies on parts falling through gaps in the track. Similar work (Goemans et al., 2006), and (Goemans et al., 2007) and (Goemans and van der Stappen, 2008), later introduced additional traps and algorithms, but all these works also model part motion as quasi-static which does not account for the uncertainty in part motion caused by the vibrations. When they in (Goemans and van der Stappen, 2008) find discrepancies between model and experiments this is accredited to unrealistic part motion.

The approach presented in this paper uses dynamic simulation similar to (Hofmann et al., 2013) and (Mathiesen et al., 2018), which we believe better encapsulates the stochastic nature of part motion in the real feeder. However, our approach differs from all previously mentioned automated design approaches as it requires no prior knowledge, or decisions, by the designer on how the part is to be oriented, but rather lets the Genetic Algorithm find out on its own.

Genetic algorithms have previously been applied to the domain of part feeder design, but on the different issue of trap sequencing. The work of (Christiansen et al., 1996) applied a GA to this problem. The GA worked on a set of pre-computed matrices describing the transition of the parts orientations when subjected to a trap, and efficiently combined these to form a sequence of traps that fully oriented the part to one specific orientation. It should be mentioned that further work has been done on this topic in (Mathiesen and Ellekilde, 2017) and recently in (Stocker et al., 2019), but as this is not directly connected to the topic of this paper, we will merely leave these references for completeness.

3 LEARNING STRATEGY AND TOOLS

This section serves to provide an overview of the applied strategy to learn a functional feeder design. As mentioned earlier, the strategy is based on a genetic algorithm which evaluates a feeder design using dynamic simulation. The overall structure of the strategy is as follows:

1. Initialize random population of P individuals[1].
2. For each generation:
   (a) For each individual, perform:
      i. Feeder Construction.
      ii. Feeder Simulation.
      iii. Fitness Computation.
   (b) Repeat P times to form the new generation:
      i. Select a parent-pair.
      ii. Generate child from parent chromosomes.
      iii. Add child to the new generation.

The core of the learning strategy lies in the genetic algorithm which explores the feeder design space. This, and details on chromosome encoding, are described in Section 4, whereas the following subsections elaborate on the feeder construction and simulation approaches used to evaluate the specific designs formed by the GA.

3.1 Feeder Construction

The feeder constructor takes as input a structured list of 2D-points and distances, and converts it to a 3D-model that can be simulated. Figure 2 shows the overall construction process.

First, a list of 2D-points seen in Figure 2a can be used to draw a closed shape in 2D by connecting each point with its two neighbors in the list. This shape will be referred to as a feeder *cross-section*, and an example of this process can be seen in Figure 2b. A wireframe can now be formed from introducing additional cross-sections (displaced along, and with its surface normal along, the direction of conveying), and connecting the points in the cross-sections which share

[1]Please note that when referring to populations and generations the population is always currently existing. The term generation is used when referring to the population in chronological context i.e. past, present, and future generations.

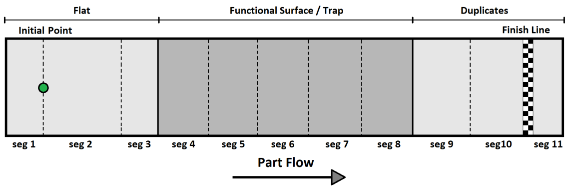


Figure 3: Illustration of the feeder layout showing the initial point from where parts start and the finish line. Marked in dark gray is the functional surface on which the constructed trap is located.

the same index. This forms a structure which will be referred to as a *feeder segment*. An example of this is found in Figure 2c. Each set of four adjacent points in the wire-frame are then closed using two triangles as seen in Figure 2d. Finally, segments are combined to form the feeder surface as shown in Figure 2e. All segments in the feeder have a specified *Segment Height*, *Segment Width*. Additionally, we also constraint the length of th the feeder by a *Min Segment Length* and *Max Segment Length* (length being in the direction of part flow). For convenience our explanation of feeder construction assumes a linear track, but bowl feeders are easily formed from this when the direction of conveying instead is transformed to the tangent of a circle. This naturally also introduces the *Bowl Radius* as a design parameter.

The track constructor works with three different types of sections, which relative placement to each other is shown in Figure 3:

- **Flat** - The section which leads the parts from start to the trap. This section forms a flat track.
- **Functional Surface/Trap** - The section which the GA will mold into a trap that orients the part. This surface is defined by its *Number of Cross Sections*, along with the number of *Points pr. Cross Section*.
- **Duplicates** - The section which leads the reoriented parts away from the feeder. Here each cross-section is a copy of the last cross-section in the functional trap.

3.2 Track Surface Smoothing

The feeder constructor tends to form surfaces with abrupt transitions and sharp edges which in general makes the designs fragile and hard to produce. This issue is addressed through the development of a smoothing operator, as an attempt to push the search space exploration towards better designs. The smoothing operator works by removing points in all cross-sections of the feeder. Excluding the four corner points which are kept fixed, the smoothing operator goes through each point on the feeder surface and removes it at a probability p_s, thus simplifying the surface and dampening the undesired features. To keep the same number of points for the next generation, the removed points are reconstructed through a linear interpolation using the points that persisted.

Therefore a p_s of 0 will have no impact on the surface, whereas a p_s of 1 will construct a completely flat surface defined by the four corner points of the surface. How the GA adapt this parameter dynamically to create good feeder tracks will be described in greater detail in Section 5.

3.3 Feeder Simulation

The constructed tracks are evaluated using dynamics simulation. The implementation is based on the robotics simulation framework RobWorkSim (Joergensen et al., 2010), which provides an interface to, among others, the physics engine ODE[2]. RobWorkSim also contains efficient methods for collision detection and contact generation, which as such provides a simulation environment sufficiently fast and accurate to model the dynamics of the system in question (Mathiesen et al., 2018).

The parts move by oscillating the feeder with a sinusoidal motion both vertically and in the direction of part flow. Forward conveying is therefore purely a result of the impact force and friction between the track and the parts. Although the simulation is inherently deterministic, this approach together with small perturbations on the initial conditions allows it to sufficiently incorporate the stochastic nature of the parts as they move along the feeder track, and thus provides a realistic environment for the GA.

3.4 Evaluation by Simulation

The simulation procedure used to evaluate the performance of a feeder design is broken up into the following steps:

1. The part is spawned at the initial point shown in Figure 3 with a random orientation as close to the surface as possible.
2. The simulation runs until it reaches a termination criteria.
3. The part's *initial* and *final state* is saved.

The simulation terminates if one of the following criteria are met:

1. The part reached the finish line.
2. The part fell off the track.

[2]The Open Dynamics Engine manual can be found at: http://ode.org/wiki/index.php?title=Manual

3. The simulation time exceeds a predefined threshold, hence the part got stuck on the track.

The *initial state* of the part represents its position and orientation (*pose*) at the initial point, whereas the part's *final state* is its pose when it got the farthest on the feeder (ideally reaching the finish line). The overall layout of the track can be seen in Figure 3.

The feeder will be evaluated over N simulations. Each successful simulation will thus produce two transformation matrices, namely the initial transform T_i and the final transform T_f, organized as a $2 \times N$ matrix:

$$\begin{bmatrix} T_{i,1} & T_{i,2} & \cdots & T_{i,N} \\ T_{f,1} & T_{f,2} & \cdots & T_{f,N} \end{bmatrix} \tag{1}$$

4 THE GENETIC ALGORITHM

A part starts on the feeder in some random orientation. Looking at the orientations of all the parts being fed, they occur with some probability distribution that we denote as the *initial distribution of orientations*. The purpose of the genetic algorithm is to transform this distribution of orientations, into an as concentrated a final (post trap) distribution as possible. In this work we do not use the notion of a finite set of distinguishable orientations, as doing so will inhibit any attempts to directly obtain a quantifiable measure of how close two orientations are to one another. Therefore, part orientations are treated as rotations about the origin in three-dimensional Euclidean space. Thus, the GA has to cluster these rotation as densely as possible and into as few disconnected clusters as possible. Albeit there are other components, this makes up the main part of the fitness function with which the algorithm operates.

4.1 The Fitness Function

This GA uses a multi-objective fitness function, from which the total fitness is calculated as the summed total of three individual fitness scores. The three fitness functions are a collision-based fitness F_C, a distance-based fitness, F_D and an orientation-based fitness F_O.

The **collision-based fitness** F_C is computed as the amount of triangles in the feeder being in collision (overlaps) with one another, negated. Feeder designs with fewer collisions c, will thus have a higher collision-based fitness described by:

$$F_C = -c \tag{2}$$

The **distance-based fitness** F_D is computed as the average distance between the part at its final state, and the goal, measured in segments along the direction of part flow.
This can be calculated as shown in:

$$F_D = -\frac{1}{N}\sum_{i=1}^{N} d_i \tag{3}$$

N is the total number of simulations and d_i is the distance from the part's final positions to the finish line. As an example, a score of $F_D = -1.3$ would indicate that, on average, each part failed to pass the last segment plus the remaining 30 percent of the second to last segment. The part's positions will be derived from the result matrix of (1).

The **orientation-based fitness** F_O is computed by measuring the average distance between all pairs of orientations. This is done by computing the difference between the concentration of the initial orientations $O(i)$, relative to that of the final orientations, $O(f)$. This results in:

$$F_O = O(\mathbf{f}) - O(\mathbf{i}) \tag{4}$$

Here, **f** and **i** represents the final and initial state being the rows in the result matrix of (1). A positive F_O will, therefore, indicate that the set of parts terminated in a more ordered state compared to when they entered the feeder.

The distance between any pair of orientations are found by computing the rotation between the two represented as an Axis-Angle rotation (AA_{rot}), thus obtaining the smallest possible rotation that separates them. The concentration of a set of orientations can then be computed as:

$$O(x) = -\frac{2}{N^2 - N}\sum_{j=1}^{N-1}\sum_{k=j+1}^{N}\sqrt{AA_{rot}(T_{x,j}, T_{x,k})} \tag{5}$$

The square root of the distance between orientations reward grouping orientations together, over simply moving all orientations closer to a mean. A perfectly concentrated set of orientations will therefore have an $O(x) = 0$ and decrease as the orientations becomes more misaligned.

4.2 The Parameter Encoding

All parameters for the optimization are stored as a binary string, which will be referred to as the *Chromosome*. Thus, each individual in a population has its own chromosome. Furthermore, the full chromosome holds multiple *Genes*, that is, sub-strings containing parameters of a specific type or length, which again can be further subdivided in to single parameters. Breaking the genetic material up into smaller

Figure 4: Representation of the chromosome structure.

components creates structure and also allows for the use of customized crossover and/or mutation schemes (see Section 4.3.3).

Each gene represents a decimal number (referred to as a *double*), ranging from $0-1$, and its binary string is encoded using b bits of reflected binary code (Gray code). The feeder segments are made from cross-sections of connected 2D-points, each point is encoded as two doubles representing its two components x an y respectively.

4.2.1 The Problem Encoding

The constructed feeders presented later in Section 6 uses the 3-gene setup represented in Figure 4. The first gene holds the points used to represent each cross-section in the feeder. The second gene holds the distances between each cross-section. Both the first and second gene is encoded as doubles of length $b = 10$, and the third gene holds the strategy parameters used for generating the children/individuals of the next generation. These values are encoded using doubles of length $b = 20$.

4.3 The Strategy Parameters

After the evaluation of all individuals of the current generation, denoted $\mathbf{g}_i$, a number of individuals are chosen using a tournament-based selection strategy. These are paired for the *recombination* step, where each parent-pair is subjected to a crossover and a mutation scheme to create the children, which make up generation $\mathbf{g}_{i+1}$.

4.3.1 The Selection Scheme

The Genetic Algorithm uses a deterministic tournament selection with no elitism. The tournament selection is applied to an evaluated population and works by randomly picking s individuals with replacement. The winner of this tournament is determined as the individual with the highest fitness, which then becomes one of two parents needed for recombination. This process is repeated to gain the second parent forming a parent-pair. This parent-pair gets one child for the new generation. This process is then repeated until the size of the new generation $|\mathbf{g}_{i+1}|$ is equal to $|\mathbf{g}_i|$.

Algorithm 1: The State-Based Crossover Scheme used during recombination.

```
// Both parent and child holds a chromosome,
   represented as a list of bits

procedure SBX(parent_1, parent_2, p_x)
    child = parent_1
    crossoverState = true
    for i = 1 → |parent_1| do
        if randReal(0,1) < p_x then
            crossoverState = randBool()
        end if
        if crossoverState then
            child[i] = parent_2[i]
        end if
    end for
    return child
end procedure
```

4.3.2 The Crossover Scheme

We refer to the crossover scheme used for this implementation as State-Based Crossover, or *SBX*. This crossover strategy allow for multiple crossover points so that with probability p_x any point in the gene becomes a crossover point. The implementation of this scheme is shown in Algorithm 1.

4.3.3 The Mutation Schemes

The mutation scheme takes as input a string of binary numbers (a gene) and manipulates it, using a mutation probability/rate p_m. This p_m, is the sum of two mutation probabilities, namely a dynamic mutation probability p_{dm}, and a static mutation probability p_{sm}. The dynamic mutation probability is the mutation rate that will be regulated by the Genetic Algorithm's self-adaption, which will be described in detail in Section 5. The static mutation probability is a constant value ensuring $p_m > 0$, which otherwise results in mutation becoming impossible for an individual. Otherwise, if the mutation rate would become 0 for a significant part of the population it could result in the learning going into stagnation. This GA implementation applies two different mutation schemes, that is Binary Uniform Mutation and 2D-Point Mutation.

Binary Uniform Mutation (BUM) This mutation scheme works by iterating through each bit in the gene, and with probability p_m, replacing that bit with a random binary number. The Binary Uniform Mutation scheme is applied to the genes containing the distances between each cross-section, and the genes containing the strategy parameters ($gene_2$ and $gene_3$).

2D-Point Mutation (2DPM) Instead of going through each bit, mutating them one by one as in the Binary Uniform Mutation, the 2D-Point Mutation scheme operates on all bits of a single point (i.e. the x- and y-component) at the same time. A mutation of the point can happen up b times with p_m probability. When a mutation happens it draws two random bit indices (one for x and another for y) and replaces the value of each bit with a random binary number.

5 SELF-ADAPTION STRATEGY

A general drawback when using Genetic Algorithms is that its performance is sensitive to the tuning of its *strategy parameters*. To remedy the problem, this implementation uses a self-adaption strategy. This means that the GAs strategy parameters will be tuned automatically, while solving the task. This self-adaption use individual level self-adaption as described in (Meyer-Nieberg and Beyer, 2007). These strategy parameters are: the crossover rate p_x, the dynamic mutation rate p_{dm}, and the smooth rate p_s. Including p_s allows for the algorithm to autonomously exploit the smoothing property to first generate smooth, but functional, feeders faster, and subsequently turn down the smoothing to opt for more detailed geometries. These strategy parameters are located at the third gene of each individual, and will be optimized along with the rest of their chromosome, using the fitness scores in combination with the selection scheme. The self-adaption is therefore said to operate on an empirical update rule as described in (Meyer-Nieberg and Beyer, 2007).

A clear advantage of the self-adaption strategy is that it makes the GA more robust and simpler to operate from a user perspective. However, the additional overhead added to the learning problem effectively slows down the algorithm as more generations now will be needed solve the same problem.

The GA's self-adaption mechanisms are applied when the new generation is formed. The strategy values of each parent forms the basis for the strategy values of their child. This is found by computing the geometric mean between the parents' strategy values by:

$$A(x_1, x_2, \ldots x_k) = \left(\prod_{i=1}^{k} x_i\right)^{\frac{1}{k}} \qquad (6)$$

The result is subjected to crossover and mutation to form the new strategy values, which are then used to

Algorithm 2: The transition function (TF) that passes genetic material from parents to child.

// Define Parents as Arrays of the 3 Genes
parent$_1[3] = \{gene_1, gene_2, gene_3\}$
parent$_2[3] = \{gene_1, gene_2, gene_3\}$

procedure TF(**parent**$_1$, **parent**$_2$, p_{sm})
    // Define Child as Array of 3 Genes
    child$[3] = \{gene_1, gene_2, gene_3\}$

    // Decode Strategy Values from each Parent
    $[p_{x1}, p_{dm1}, p_{s1}] \leftarrow decode(\mathbf{parent}_1[3])$
    $[p_{x2}, p_{dm2}, p_{s2}] \leftarrow decode(\mathbf{parent}_2[3])$

    // Compute the Geometric Mean
    $p_x = A(p_{x1}, p_{x2})$
    $p_{dm} = A(p_{dm1}, p_{dm2})$

    // Generate Child's New Strategy Values
    $\mathbf{child}[3] = SBX(\mathbf{parent}_1[3], \mathbf{parent}_2[3], p_x)$
    $\mathbf{child}[3] = BUM(\mathbf{child}[3], p_{dm} + p_{sm})$
    $[p_x, p_{dm}, p_s] \leftarrow decode(\mathbf{child[3]})$

    // Recombination, Mutation and Smoothing
    $\mathbf{child}[2] = SBX(\mathbf{parent}_1[2], \mathbf{parent}_2[2], p_x)$
    $\mathbf{child}[2] = BUM(\mathbf{child}[2], p_{dm} + p_{sm})$

    $\mathbf{child}[1] = SBX(\mathbf{parent}_1[1], \mathbf{parent}_2[1], p_x)$
    $\mathbf{child}[1] = 2DPM(\mathbf{child}[1], p_{dm} + p_{sm})$
    $\mathbf{child}[1] = SurfaceSmoothing(\mathbf{child}[1], p_s)$
    return child
end procedure

generate the remaining ($gene_1$ and $gene_2$) genes by applying *SBX*, mutation, and finally smoothing.

This is done when applying the transition function of Algorithm 2 to the parent-pairs chosen by the selection scheme. The function takes as input two parents (each with the three genes), and the static mutation rate p_{sm}.

6 RESULTS

This section presents the result from testing the feeder design approach on two parts, whereas Section 7 will serve to discuss these result. The two parts are: 1) A $4 \times 8 \times 12\,mm$ solid plastic *Cube* and 2) an industrial brass part which will be referred to as *Cone*. The two parts can be seen in Figure 5, placed on a flat track, in the simulation environment, oriented in their stable poses.

The vibratory drive unit used for the experiments is a *BF40* vibration drive, controlled using a *Fre-*

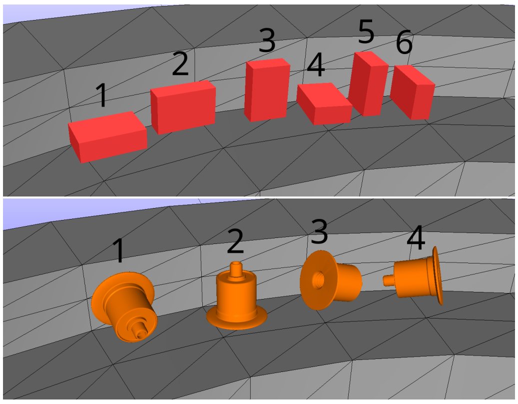


Figure 5: The two parts, the cube (top) and the cone (bottom) in their poses. The parts' stable poses are numbered from left to right.

Table 1: The list of manual settings used for learning the designs for both the cube and the cone.

	Cube	Cone
Number of Cross Sections	5	5
Points pr. Cross Section	8	8
Min Segment Length	15 mm	22 mm
Max Segment Length	36 mm	36 mm
Segment Width	60 mm	60 mm
Segment Height	30 mm	30 mm
Bowl Radius	175 mm	175 mm
Simulations/Evaluation [N]	100	100
Population Size [P]	100	100
Tournament Size [s]	6	6
Static Mutation Rate [p_{sm}]	0.002	0.001

quency control unit SIGA, from the manufacturer *Afag Automation AG*[3]. The drive has a vibration angle of 12° and operates at 50Hz full-wave motion. The physical properties: parts mass, friction coefficient, and restitution coefficient between part and feeder has been determined experimentally. All these parameters are used to model the system in simulation.

The GA and feeder track constructor also has a list of settings. The chosen settings for the two test-cases can be seen in Table 1.

6.1 Learning Feeder Designs

The GA is used to learn a feeder design for each part. The graphs in Figure 6 show how the fitness evolve over time for the cone part. The learning graphs for the cube was left out intentionally, as it has very similar characteristics. However, it convergence on a working design around generation 60. Here each graph shows the learning curve of the best performing individual in a population, along with the arithmetic mean of the top 30th percentile of the population.

Figure 7 shows how the strategy values adapt over time. This is shown with the geometric mean of the top 30th percentile of the population.

The learning is time-consuming, mainly due to the evaluation step, so evaluations are run in parallel on a computer cluster[4]. The learning ran for a total execution time of 16.5h and 35.5h, for the cube and the cone, respectively, which resulted in 467 generations for both.

6.1.1 Selecting the Final Solutions

At the end of each generation, the highest performing individual in the population is stored, effectively forming a list of population winners. The highest scoring individuals in this list are reevaluated each with 1000 simulations and a new winner is chosen as the best feeding solution.

The best solution for the cube was found in generation 439 and in generation 462 for the cone. The corresponding model of these feeder designs can be seen in Figure 8. 3D-printed[5] versions of these solutions were used for validation with real-world experiments and are shown in Figure 1.

6.2 Feeder Validation

The best feeder designs were validated through real-world experiments on the physical feeder. This was done using the *stable poses* for the cube (6 poses) and the cone (4 poses) shown in Figure 5, and testing success rate over a fixed number of experiments for each stable pose. A success is defined as the part ending up in the expected orientation.

Results comparing simulation and real-world experiments for both the cube feeder and the cone feeder is found Table 2 and Table 3, respectively. Here, T is the number of Tests performed, F counts the number tests which Failed, and the Performance P is the success rate measured in percent. A failed test is defined as when the part does not ends up in the expected orientation (as shown in Figure 8).

7 DISCUSSION

The learning curves in Figure 6 show that the GA manages to improve the feeder design across the gen-

[3] See https://www.afag.com/

[4] The cluster consists of ten PCs each with an *Intel Core i7-3770 CPU@3.40 GHz* with 4 cores and 8 threads.

[5] The feeders were printed using a consumer-grade 3D-printer, and lightly post-processed to remove the unintentional layer lines that occurs when using an FDM printer.

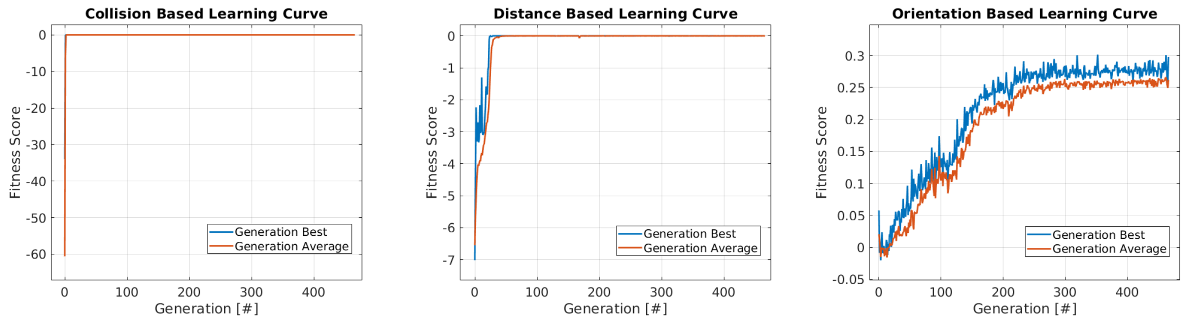


Figure 6: The learning for the cone part. The learning curve is split up into each of the three fitness scores for transparency. This is shown for the best performing individual of each generation (blue) and the average score computed from the top 30th percentile in each generation (red). Note that for the collision based score, the curves are close together.

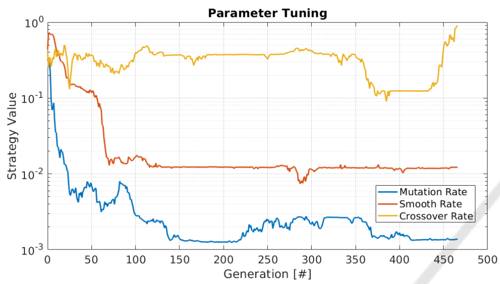


Figure 7: The evolution of the strategy values over time. The strategy values were computed as the geometric mean of the populations top 30th percentile of the population. This is shown on a logarithmic scale.

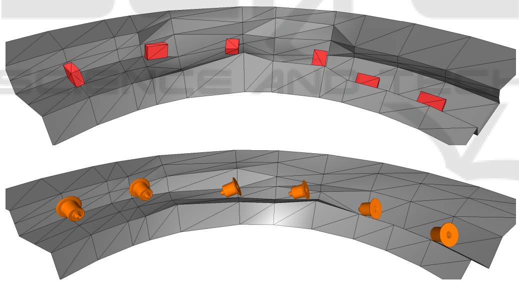


Figure 8: The final feeder designs for the cube (top), and the cone (bottom). The rightmost part on each shows the expected final orientation of the part.

erations. The algorithm quickly finds a design without collisions in its internal model. In around generation 50 the design also allows the part to move all the way from its initial starting position to the finish line. From the orientation based learning curve it can be seen that the GA steadily forms a feeder which reduces the variance of the cones orientation distribution, and that from around generation 250 the rate of convergence decreases.

Looking at Figure 7, it can also be seen that the strategy values for Mutation and Smooth rate go towards a specific range, indicating convergence, however, with some noise (which is to be expected when the self-adaption tries to improve). These strategy values gradually become less aggressive as the GA converges on a useful feeder design. However, the crossover rate behaves more erratic at the end of the learning curve. This can be explained by the fact that the individuals in the population become very similar over time. When this happens the crossover scheme will have little impact and thus the self-adaption strategy will not be able to make meaningful adjustments to this strategy parameter.

Table 2: The cube feeder test results.

	Simulation			Physical		
Pose	T	F	P	T	F	P
1	1000	0	100.0%	100	0	100%
2	1000	10	99.0%	100	0	100%
3	1000	5	99.5%	100	0	100%
4	1000	9	99.1%	100	0	100%
5	1000	7	99.3%	100	0	100%
6	1000	7	99.3%	100	0	100%
Total	6000	38	99.4%	600	0	100%

Table 3: The cone feeder test results.

	Simulation			Physical		
Pose	T	F	P	T	F	P
1	1000	25	97.5%	100	1	99%
2	1000	40	96.0%	100	3	97%
3	1000	37	96.3%	100	2	98%
4	1000	24	97.6%	100	0	100%
Total	4000	126	96.9%	400	6	98.5%

From Table 2 and Table 3 it can be seen that both feeder designs perform re-orientations with a high success rate, however, not without notable errors. This is especially clear for the cone feeder design scoring a 98.5% success rate for the experiments on the physical feeder. It should be noted that the real feeders seem more forgiving than the simulation and achieves better performance. This could simply be due to uncertainties from the limited data-set of the manual experiments, but previous experience has also shown that the simulation has a tendency to emphasize some errors that are otherwise dampened by the real feeder.

The learned feeder designs presented in Figure 1 and 8 reorients the parts by exploiting their mass distribution and attempt to topple them into one orientation. The track shape is then held constant to keep the parts in their new orientation. This removes the need for a designer to make informed decisions on the orientation strategy, both in terms of deciding on a suitable trap type, as well as deciding which part orientation to optimize the feeder towards. This results in a system which is easier to use for non-experts.

8 CONCLUSION

In this paper, a new approach to vibratory feeder design has been presented. The approach is based on a Genetic Algorithm with self-adaption of its strategy values. The approach creates working designs that attempt to reorient all parts in the feeder to a single orientation. The novelty of the approach is that it can grow free-form features adapted to the specific part, which is a clear distinction from previous methods, that optimizes fixed designs by varying their inherent parameters. The design approach was used to learn designs for two parts, where it in both cases formed features that toppled the parts and subsequently held them in place in their new orientation. The obtained designs yielded promising results with high success rates making the presented approach a solid basis for future work.

9 FUTURE WORK

There are multiple open issues that can be addressed with future work. Most notable is that the results do not provide 100% successful reorientation, and for the designs to be used in industry this needs to be handled. Moreover, the simulation accuracy, although producing useful realistic results, is not perfect. An approach to address this could be adding controlled noise to the sensitive parameters such as geometry, mass distribution, friction, etc., forcing the learning to adapt the design to account for these variations, and thus creating a more robust result.

Furthermore, the simulation involves only one part on the track. This neglects the influence of part interaction on the learned design and the effect this has is an open question that must be addressed in the future.

Additionally, even with a perfect simulation, there is no inherent guarantee in the algorithm, that it finds a perfect design using only the current strategy of reorienting the parts. Thus, it could be necessary to extend the design method with another strategy which more aggressively optimizes towards rejecting parts in all but one orientation.

It is also likely that better performance can be achieved by having specific strategy parameters of each individual gene, as e.g. the optimal value for mutation rate could be different for the distance between segments and the 2D-points of the cross-sections. Investigating this in the future could lead to faster convergence and improved performance and is essentially free to investigate due to the GA's self-adaption.

Naturally, the settings in Table 1 also affect overall performance and should be addressed with a clear policy on how to set them.

Lastly, the approach should also be validated on more test cases in the future, but in its current state, this feeder design approach shows promising results.

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