Automatic Selection and Sequencing of Traps for Vibratory Feeders

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Abstract: Vibratory parts feeders with mechanical orienting devices are used extensively in the assembly automation industry. Even so, the design process is based on trial-and-error approaches and is largely manual. In this paper, a methodology is presented for automatic design of this type of feeder. The approach uses dynamic simulation for generating the necessary data for configuring a feeder with a sequence of mechanical orienting devices called traps, with the goal of reorienting all parts from a random to fixed orientation. Then, a fast algorithm for facilitating this configuration task automatically is developed from domain specific knowledge. Finally, the algorithm is validated on three industrial cases and its drawbacks and strengths are discussed in detail.

1 INTRODUCTION

Parts feeders using vibrations as means of conveying have been a widely used concept in industrial automation for decades. This type of feeder comes in two forms being the linear feeder and the bowl feeder (illustrated in Figure 1).

The working principle for the feeders is fairly simple, using combined vertical and horizontal vibration to shake parts forward along the either straight or spiral track. On this track the parts encounter mechanisms, so-called traps, that can cause the parts to reorient or force wrongly oriented parts off the track. When used correctly, the effect of these traps are that all parts reaching the end of the track will have the same orientation, thereby being ready to be picked or fed into an automated assembly system.

Although the technology has been readily available for decades, little has changed in the approach to designing this feeder type. This task still relies heavily on trial-and-error and is done by skilled technicians, or engineers, combining experiences with significant amounts of parameter tuning on the physical system. Although some part families can be associated with some standard solution of combining specific trap mechanisms (such as caps or bolts) a high degree of customisation is often needed. This frequently result in excessively high prices even for basic feeding solution due to the cost of the manual labour put into designing and testing the feeder.

Figure 1: CAD-model of a vibratory bowl feeder.

Researchers have investigated the topic of feeder design before, but to our knowledge a holistic solution for automatic design of vibratory feeders is still lacking. The overall aim of this work is to produce such an automatic solution, for which a general methodology is presented in Figure 2.

The proposed method is inspired from (Mathiesen and Ellekilde, 2016) and (Hansson et al., 2016), but will not rely on precomputed data for generic object categories. The four steps in the proposed method are therefore:

1. Classifying the part to be fed to a family of parts with the purpose of determining suited trap principles.
2. Setting the trap parameters for the specific part and potentially optimising these using simulation.

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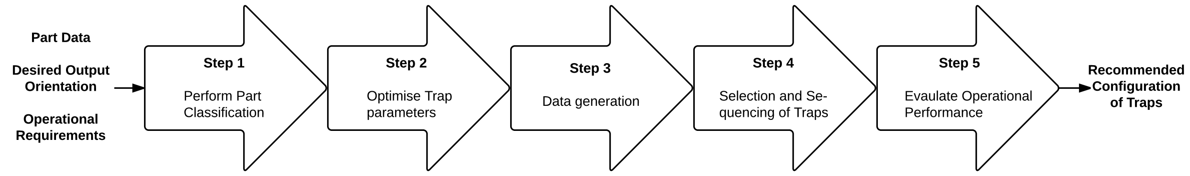


Figure 2: Design methodology for automatic configuration of vibratory feeders.

3. Producing the behavioural data for traps through simulation of the part interacting with these traps.
4. Using this data to automatically select the best sequence of traps that orients the part.
5. Evaluate the performance of the solution against requirements (orienting capability, feed rate, etc.).

In this paper we specifically address steps 3 and 4 of automatically finding feeder configurations. Steps 1 and 2 are done according to (Boothroyd, 2005).

The remainder of the paper is structured as follows: Relevant literature on previous work are reviewed in Section 2. Section 3 presents the proposed approach for generating behavioural data and the algorithm for automatic selection and sequencing of traps. This is followed by test results in Section 4 and general discussion, conclusion and future work in Sections 5 and 6.

2 RELATED WORK

The work of (Boothroyd, 2005) is an extensive collection of work with guidelines for aiding in the design of vibratory bowl feeders. The work covers the mechanics of the vibratory bowl feeder in detail, but also provides an extensive appendix on part classification for mapping specific part features (e.g. protrusions, holes. etc.) to mechanisms potentially utilising those features to orient the part.

Other researches have also investigated the use of guidelines to help designers. An expert advisory system is presented by (Tan et al., 1995) for the selection of traps to orient parts. This expert advisor uses data from a part classification system to provide an user with suggestions on feasible traps. A similar rule-based system capable of suggesting traps is presented by (La Brooy et al., 1995), where relevant part features are extracted directly from the CAD-model of the part, thus eliminating the need for designers to manually be able to classify the part.

The works described above are based on knowledge obtained from formalised prior experiences and extensive testing on physical hardware and are useful to guide the conceptual design of the vibratory feeders. Specifically, the work of (Boothroyd, 2005) also delivers approximations of how to set the internal parameters of a number of trap mechanisms to obtain the desired orienting capabilities. Even so, the only way to fully validate the performance of a feeder design is to construct it. Doing this physically is time-consuming and costly and therefore greatly merits the use of simulation for prototyping and data acquisition as discussed in (Mathiesen and Ellekilde, 2016) and (Hansson et al., 2016).

Using simulation to model and validate designs of vibratory feeders is not a new concept. (Berkowitz and Canny, 1996) and (Berkowitz and Canny, 1997) investigated the interaction between one trap mechanism and two types of parts being cuboids and cylindrical. Their work presented an overall consistency between their prediction in simulation and experiments on a physical test platform, although with some differences. (Jiang et al., 2003) developed a custom simulation software for vibratory bowl feeders and validates the performance of a trap with varying operational parameters for rejecting wrongly oriented cuboids. In recent work (Stocker and Reinhart, 2016) the Bullet Physics Engine (Coumans, 2010) is used to model part behaviour in a vibratory feeder. Here they investigate the efficiency of a step mechanisms and the correlation between this efficiency, the height of the step and the length of the part.

In the literature, simulation has primarily been used to validate a trap design, with some parameters manually set by a designer, but in the work by (Hofmann et al., 2013) an algorithm is presented for automatic parameter optimisation of trap mechanisms. This work also uses dynamic simulation for evaluation of trap performance and, in addition to the geometric shape of the trap, also incorporates the vibrational amplitude into the optimisation. Their optimisation algorithm have been tested with a single step trap, feeding a cuboid and a cylindrical-like object.

Another approach to optimisation of trap parameters is presented in (Berretty et al., 2001). They developed an algorithm based on computational geometry for finding good parameter values for four different trap mechanisms. Common for all four traps is that they work by letting wrongly oriented parts fall through a gap in the feeding track, but using only this type of trap, the authors show that their algorithm can find traps correctly filtering out wrong orientation of a complex industrial part. A similar approach to trap design is found in (Goemans et al., 2006) which presents an algorithm for finding the parameters for a trap family of blades.

Automatic optimisation of the parameters of individual traps has been explored to some degree, but little work has been done in the automatic selection and sequencing of these mechanisms beyond the rule-based suggestion systems listed in the beginning of this section. This is with the exception of (Christiansen et al., 1996) who tackles the problem using a Genetic Algorithm (GA) approach. Their algorithm finds good feeder designs, but due to the GA approach optimality is not guaranteed. The input data for the algorithm is based on results from (Murch and Boothroyd, 1971) and (Boothroyd, 1992) (earlier version of (Boothroyd, 2005)), in the form of several matrices mapping the input orientations to output orientations of a part. In their work (Christiansen et al., 1996) express plans to augment their approach with automatic generation of the required input data for the algorithm, but to our knowledge these plans where either not pursued or successful.

3 AUTOMATIC CONFIGURATION OF VIBRATORY FEEDERS

Assuming a finite number of possible orientations of a part on the track, the work of (Murch and Boothroyd, 1971) and (Boothroyd, 2005), presents how the behaviour of a trap can be encoded into a stochastic transition matrix mapping an observed input orientation distribution to an output distribution. An example of such a transition matrix is given in (1)

$$T = \begin{array}{c c} & \begin{array}{cccc} O_1 & O_2 & \dots & O_N \end{array} \\ \begin{array}{c} O_1 \\ O_2 \\ \vdots \\ O_N \end{array} & \begin{bmatrix} P(O_1|O_1) & P(O_2|O_1) & \dots & P(O_N|O_1) \\ P(O_1|O_2) & P(O_2|O_2) & \dots & P(O_N|O_2) \\ \vdots & \vdots & \ddots & \vdots \\ P(O_1|O_N) & P(O_2|O_N) & \dots & P(O_N|O_N) \end{bmatrix} \end{array} \tag{1}$$

where O_i represents the different orientations and $P(O_j|O_k)$ is the probability of ending in orientation O_j given it starts in O_k.

When multiple traps are placed in sequence the combined behaviour can be obtained by simple matrix multiplication of the transition matrices. Given an initial distribution, p_{init}, as a row vector, of orientations of the parts on the track and a sequence of M traps with transition matrices T_i the output distribution p_{out} can be computed as:

$$p_{out} = p_{init} \prod_{i=1}^{M} T_i \tag{2}$$

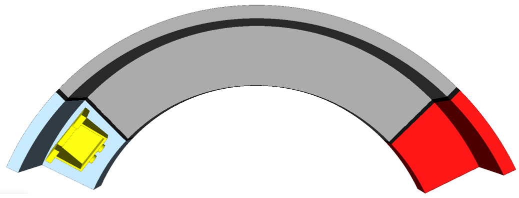


Figure 3: To obtain data mapping input orientations to output orientations parts are simulated conveying from the *Starting area* (blue), across the *Trap area* (grey) to the *Target area* (red).

The method is straight forward, but has a problem with availability of data. Constructing the transition matrices requires observations on how a part interacts with a trap. First, for the method to be reliable, a significant amount of observations are needed and manually acquiring the necessary magnitude of data is impractical. Secondly, these matrices are highly dedicated to a specific part-trap pair as well as the specific parameter settings for that trap. Physically building the traps for orienting a specific part and next observing the performance of each is hence an infeasible strategy, thus we suggest the use of dynamic simulation of the vibratory feeder to produce the data efficiently as discussed below.

3.1 Generating the Transition Matrices

In our earlier work (Mathiesen and Ellekilde, 2016), dynamic simulation of vibratory feeders were analysed when using the physics engine ODE v0.13 (Smith, 2006) together with the simulation environment RobWorkSim (Joergensen et al., 2010). Using the same simulation environment and physics engine, and knowing the possible orientations of the part, the transition matrices for a part-trap combination can be generated automatically.

Figure 3 illustrates a piece of the feeder track with three marked areas: 1) *Starting area* (blue), 2) *Trap area* (grey), 3) *Target area* (red). As the name indicates, traps are inserted into the *Trap area* with the purpose of interacting with the parts and potentially reorient or reject them. Any non-rejected part will reach the target area where its resulting orientation can be saved. This final orientation of the part is paired with its initial orientation prior to interacting with the trap.

The transition matrix is then constructed by matching the two orientations to the defined set of orientations of the part as follows:

1. If the part is rejected by the trap, increment the rejection counter for that starting orientation index.

2. If not rejected, find in the defined set of orientations the best matching for the the pre- and post-trap orientations and update the corresponding element in the transition matrix.
3. Normalise each row together with its corresponding rejection counter (unless all elements in equal 0).

When finding the best matching orientations it is important to compensate for the rotation of the track, such that the part orientation is found relative to the direction of the track.

It is important to note, that not all traps consists of a transition between two pieces of the original track type (e.g. a flat track, the a trap and then the same flat track). An example is the trap consisting of a groove, which can be used to catch a part by its protrusion. For this trap to function, the track is tilted at an angle towards the centre of the bowl effectively making parts, not caught in the groove as intended, slide off the track. In this case, the tilt angle of the track must be accounted for in the matching, which should therefore not only consider the direction of the track but also the normal.

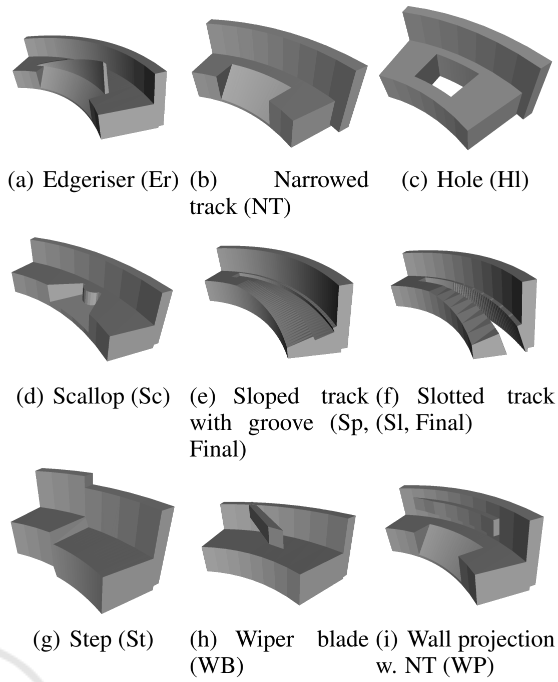
In this work a total of nine trap principles are used. These are illustrated in Figure 4. The set of nine traps are chosen to be sufficient for describing the algorithm. The sloped track with groove and the slotted track are treated as *final traps* as none of the other traps can succeed them due to the before mentioned angling of the track. For convenience, abbreviations for the traps are listed in the captions.

3.1.1 Dealing with Rotational Symmetry of Parts

Some parts, like discs and cylinders, are symmetric around an axis of rotation, which needs to be accounted for in the method for automatically matching observed orientations. For this a so-called *orientation group* is defined to represent a set of orientations only differing in a rotation around the symmetry axis. A practical implementation of such a group is as a list of orientations representing the set, then a match to the orientation can be found to the best sample within this set.

3.2 Selecting and Sequencing Traps

The transition matrices allows combining the functionality of the traps into a feeder configuration (sequence of traps), thus estimating the functionality of a specific sequence of traps. The proposed search strategy consists of dynamically constructing a tree, where each node represents a feeder configuration and has



(a) Edgeriser (Er) (b) Narrowed track (NT) (c) Hole (Hl)

(d) Scallop (Sc) (e) Sloped track with groove (Sp, Final) (f) Slotted track (Sl, Final)

(g) Step (St) (h) Wiper blade (WB) (i) Wall projection w. NT (WP)

Figure 4: All nine trap principles used in this work. Listed with abbreviations for further reference and marking of "Final" to indicate a final trap.

an associated output distribution of orientations encoded as a row-vector p_{out} and a rejection rate p_r. For the root the distribution will be the expected initial distribution of parts on the track and the rejection rate will be 0. Edges in the tree now represents different traps and when branching to a new node, the transition matrix of the trap is post-multiplied on the distribution vector of the parent, given the expected output distribution for the child.

$$p_{out,child} = p_{out,parent} T_{trap} \tag{3}$$

The probability of rejection can be obtained from p_{out} by (4).

$$p_r = 1 - \sum p_{out} \tag{4}$$

$$\tag{5}$$

A quality score, Q, of the configuration can now be calculated using (7):

$$\hat{p}_{out} = \frac{p_{out}}{|p_{out}|} \tag{6}$$

$$Q = (1 - p_r) p_{CO} \tag{7}$$

where p_{CO} corresponds to the correctly oriented parts within $\hat{p}_{out}$. The best quality which can be achieved is $Q = 1$ and is when all parts are oriented correctly and no parts are rejected in the process.

In many cases it can be an advantage to not look for a specific orientation, but see which orientation gives the most efficient output. In this case p_{CO} in (7) can be replaced by $max(\hat{p}_{out})$.

The algorithm described above is essentially a non-informed exhaustive search strategy and complexity scales exponentially with the length of the sequence of traps. In general, a feeder configuration is not limited to contain just a single instance of a trap. This is because of some traps having probabilistic behaviour. This means, that a trap can map one input orientation to multiple output orientations with different probabilities, e.g. a *Step* where parts can end in multiple orientations, but with a potential bias based on their shape and distribution of mass. In these cases, repeating the same trap multiple times could be needed for reducing the probability of an undesired orientation. Therefore, the maximum allowed search depth, M, must be bounded to some finite value for the algorithm to terminate. Furthermore, the amount of different traps, N, which can be applied to orient the part also impact search time for the algorithm. The actual size of the tree, $\mathcal{T}$, to explore for finding a feeder configuration is therefore given by (8):

$$|\mathcal{T}| = \sum_{j=1}^{M} N^j \tag{8}$$

Searching through all possibilities will have an exponential and infeasible running time. However, by realising that a solution can never achieve a higher quality score than its probability of rejecting the part, branches of the tree can efficiently be pruned away. This is done by comparing the $(1-p_r)$ value for a node with the quality of the currently known best solution. In the pseudocode of Algorithm 1 this is implemented by not adding the non-promising node to the queue where non-evaluated nodes are held. Furthermore, the same check is made after a node is taken from that queue as it could potentially have been added before the current best solution was found. The queue is implemented as a priority queue always having the element with highest Q as the first element. In addition to this branch closing strategy, an upper bound for p_r can be given to the algorithm to disregard solutions rejecting too many parts to be feasible. All sub-branches to a trap designated as final traps are also closed as no trap can follow. The purpose of a feeder configuration is to fully orient a part by forcing the probability of an orientation to 1. Since the data used for testing the algorithm in Section 4 is made from traps with hand-tuned parameter-sets they may not work optimally, hence feeder configurations that nearly does full orientation can well be applicable in a real world scenario. Therefore a margin for treating a feeder configuration as a correct solution is introduced.

Algorithm 1 Algorithm for finding suitable feeder configurations for orienting parts.

```
// Initial state: Empty queue, q, for containing
nodes and empty list, c, for feeder configurations

add(root) to q // dummy node with Q = 0
while q ≠ ∅ do
    node_cur = best(q) // max(Q)
    if depth(node_cur) < M then
        for each child node k do
            Using (2) compute p_out
            p_r = 1 − sum(p_out)
            p̂_out = p_out / |p_out| // normalise p_out
            p_CO = p̂_out,desired or max(p̂_out)
            Q = (1 − p_r) p_CO
            if p_CO ≥ m_c then
                add(k) to c
            end if
            if (1 − p_r) > Q_best then
                if p_r < p_r,max then
                    add(k) to q
                end if
            end if
        end for
    end if
end while
Return c
```

The final algorithm has three parameters that effects the result:

1. Margin for correct solution, m_c.
2. Maximum allowed probability of rejection, $p_{r,max}$.
3. Maximum search depth, M.

The maximum allowed p_r should be set according to specification from the surrounding system on required feed rate based on possible conveying speed for parts in the feeder. The max search depth must also be set according to limitations on the physical dimensions of the feeder, i.e. larger bowl diameter makes room for more traps.

The final algorithm is presented in Algorithm 1, where $\hat{p}_{out,desired}$ refers to the desired index of $\hat{q}_{out}$ when searching for a specific solution.

4 RESULTS

The algorithm described in the previous section has been used to plan sequences of traps for the parts shown in Figure 5.

Some trap principles are only applicable to certain geometric features or dimension ratios, e.g a sloped

Table 1: List of the nine traps marking, with ”x”, which were used for each part.

Trap name	Cap	Cone	Brick
Edge riser	-	-	x
Narrowed track	-	x	x
Hole	-	-	x
Scallop	x	-	-
Sloped track w. groove	x	x	x
Slotted track	-	x	x
Step	x	x	x
Wall projection w. NT	x	x	x
Wiper blade	-	-	x

track with a groove will not work if the part has no protrusion that can be caught in that groove. Therefore, data for interaction between the three parts and the traps has only been made for a subset of the nine traps, as listed in Table 1.

4.1 Stability Analysis of the Transition Matrices

The proposed approach relies on accurate estimation of the probabilities that make up the transition matrices, recall (1). To investigate how many samples are needed for this estimation to become stable, 10,000 simulations have been run for the three parts and all of their associated traps. The effect of the trap is then determined using (2), effectively resulting in the output probability distribution vectors, $p_{out,i}$, computed from T_i, where i refers to the number of samples used to create that transition matrix. We then calculate the difference between the current estimate and the previous using (9),

$$\Delta_i = p_{out,i} - p_{out,i-100} \tag{9}$$

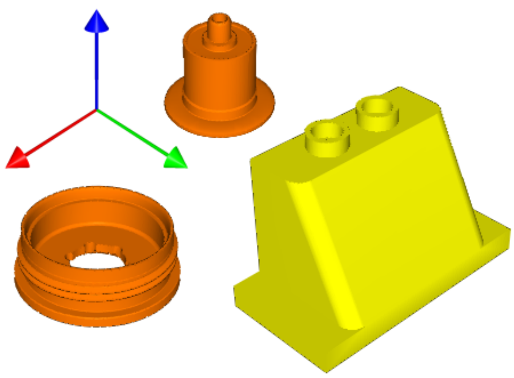


Figure 5: The three parts used as cases for this work. From left to right: Cap, Cone and Brick. Parts are shown in proportion. For reference the coordinate system is oriented as shown with origin in the centre of gravity of each part.

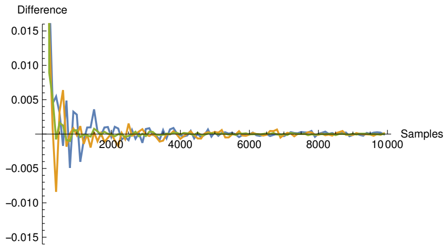


Figure 6: Convergence of the transition matrices for the three parts. The horizontal axis shows the number of samples used and the vertical the change in the output distribution, given in probability from $0-1$.

where Δ_i is computed for $i = 100, 200, \ldots, 10{,}000$ in steps of 100. For the three parts, we then take the $mean\,(\Delta_i)$ across all traps and plotted as $\{i,\ mean\,(\Delta_i)\}$ in Figure 6.

For low values of i, Δ_i is large, thus the view in Figure 6 is zoomed to the appropriate level of detail. From the graph it can be seen that Δ_i for all three parts converges to near zero values fast, but with the Cap and Cone both showing oscillating behaviour. This is also the case for the Brick, but with less amplitude. The result gradually becomes more stable, and at 4000 samples $\Delta_i < 0.001$ for all parts, indicating that less than 1‰ of the samples will change their output orientation.

4.2 Orienting the Parts

The algorithm finds the feeder configurations listed in Table 2 for the three cases. For all results shown in the table the parameters of the algorithm were set as follows: $m_c = 0.95$, $p_{r,max} = 0.9$, $M = 5$.
Recall p_{CO}, was the estimated probability of correctly orienting the part, p_r the probability of rejection and Q the quality score computed by (7). The results show, that the Cap can be oriented using a *Scallop trap* after a *Step trap*, which changes the probability towards an orientation that can pass the scallop (the orientation shown in Figure 5). For the Cone part, the found configuration consists of four *steps* and finally a narrowed track with a wall projection rejecting all Cone parts not in the upright orientation labelled O_0 in Figure 11, showing the most occurring orientations of the Cone. Using the algorithm, feeder configurations are also found for the Brick. The best solution uses a fairly involved sequence of traps to orient the part. The probability distribution after each trap is shown in Figure 7 and the dominant orientations of the Brick illustrated in Figure 8. It should be noted that a total of 24 distinct, and stable, orientations of the Brick has been observed in simulation.

First the *steps* pushes the distribution of prob-

Table 2: The four feeder configurations found by the algorithm. "Evals." denotes the number evaluations made by the algorithm and "Found i." the evaluation step that configuration was found in.

	Part	Feeder config.	p_{CO}	p_r	Q	Evals.	Found i.	Time[s]
1	Cap	$St \rightarrow Sc$	0.99	0.29	0.70	28	4	0.002
2	Cone	$St \rightarrow St \rightarrow St \rightarrow St \rightarrow WP$	0.99	0.55	0.45	95	24	0.008
3	Brick	$St \rightarrow St \rightarrow Er \rightarrow WB \rightarrow NT$	0.99	0.73	0.26	4671	1235	0.379
4	Brick	$St \rightarrow Er \rightarrow St \rightarrow Er \rightarrow WP$	1.00	0.88	0.12	7731	817	0.631

ability towards the most stable orientations. The *Edgeriser* trap attempts to raise the Brick resulting in an increase in O_0 and O_{12}. The *Edgeriser* is not successful in raising all parts and some are reoriented to O_{22}. All parts resting in the upright orientation (O_0, O_1, etc.) are then rejected by the *Wiper blade*. This leaves Bricks lying down as O_{18}, $O_{20} - O_{23}$, but due to the centre of gravity of the Brick, the *Narrowed track* can then reject all other orientations than O_{22}.

Forcing the algorithm to search for specific orientations, an alternative feeder configuration is found for the Brick that orients it to O_0. This configuration scores a lower quality due to higher probability of rejection. Feeder configuration 1,2 and 3 only achieve a score for correct orientation of the part of 0.99. This is due to the hand-tuning of the trap parameters mentioned in Section 3.

4.3 Informed vs. Non-informed Search

To show the difference between using the presented informed search compared to an exhaustive strategy the number of required evaluations needs to be considered. Figure 9 shows a logarithmic plot of the number of evaluations for the three cases, when using the informed strategy (denoted I and shown with solid lines) reducing the search space compared to the exhaustive strategy (denoted NI and shown with dashed lines). Both the informed and exhaustive strategy including the concept of final traps.

It can be seen in Figure 9, that the informed search strategy improves the number of evaluations required by several orders of magnitude. For both the Cap and Cone part, the savings with the informed method is around a factor of 10^4. For the Brick part, the relative difference is lower, but still around a factor of 10^2. Although the graphs indicate a sub-exponential runtime for the informed search, we have no formal proof and in worst-case it may still require exponential run time.

4.4 Repeating Traps

In the work of (Christiansen et al., 1996) they report a feeder configuration consisting of eight repetitions of a *Pressure break trap* (not used in this work), a *Wiper blade* and a *Slotted track*. Our algorithm finds a similar repetitive sequence for the Cone part with multiple

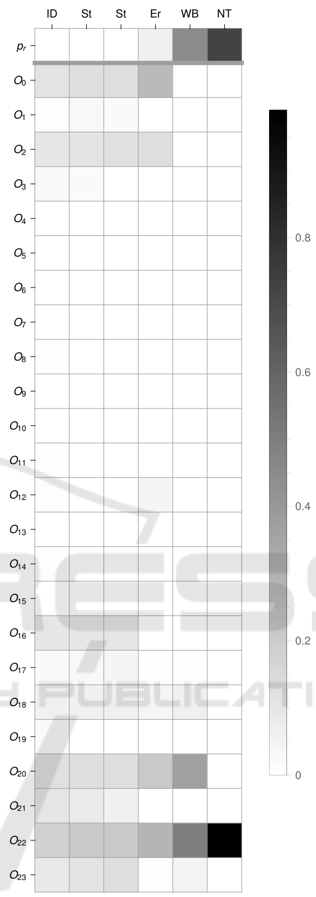


Figure 7: Step wise probability of orientations for feeder configuration 3. All O_x are the orientations and p_r the probability of rejection. "ID" denotes the initial probability distribution of orientations before any traps.

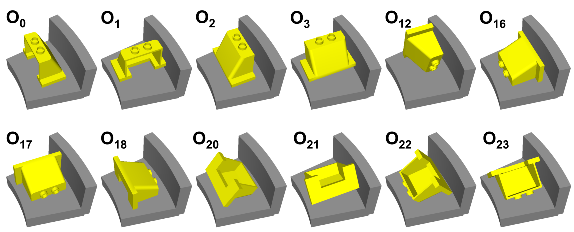


Figure 8: Illustration showing the dominant orientations and when these are effected by the traps of feeder configuration 3.

Step traps in succession. The result of applying each trap is illustrated in Figure 10, where the seven dis-

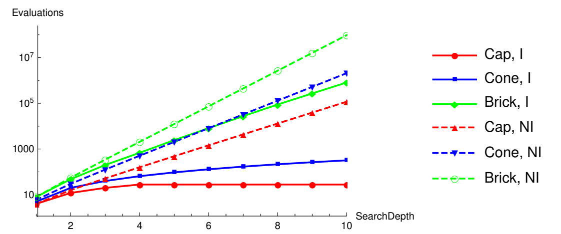


Figure 9: Run data for the search algorithm with varying max search depth, comparing the amount of evaluations made by the informed search vs the a non-informed, shown on a logarithmic scale.

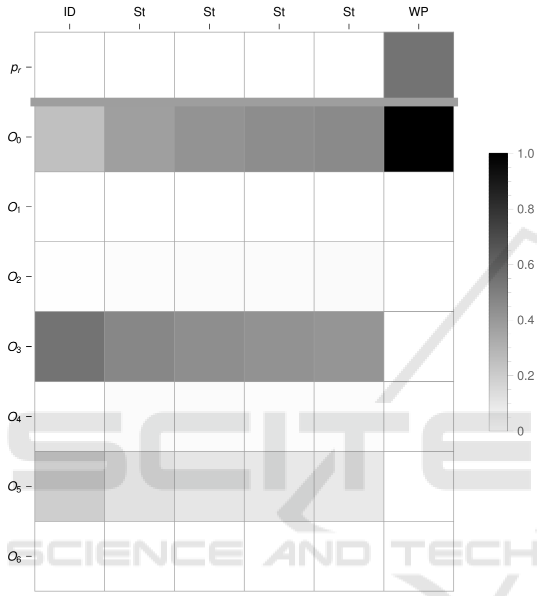


Figure 10: Step wise probability of orientations for feeder configuration 2.

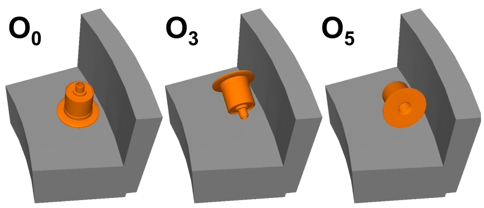


Figure 11: The three most frequent orientations of the Cone part.

tinct orientations of the Cone is visualized with the probability of occurrence shown as a grey-scale from white $P(0_i) = 0$ to black $P(O_i) = 1$. The three most frequent orientations are shown in Figure 11.

The figure show that the repetition of the *Step trap* moves the probability for orientation O_3 and O_5 towards O_0 in steps of $\approx \{0.13, 0.05, 0.02, 0.01\}$. Increasing M for the algorithm allows it to add more *Step traps* with, for each, a diminishing effect. For comparison, the improvement between configuration

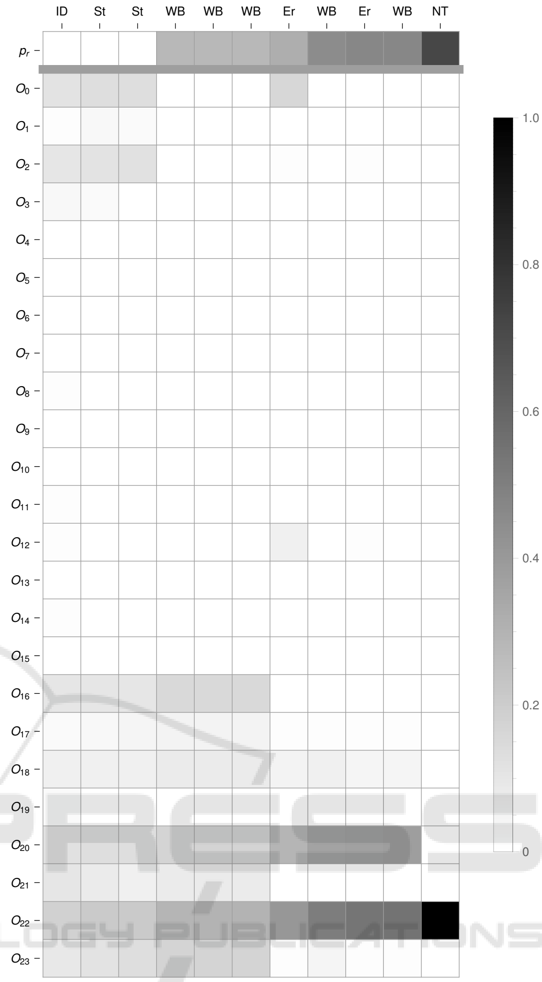


Figure 12: Step wise probability of orientations for best feeder configuration found for the Brick part when sequence length $M = 10$.

2 in Table 2 (where $M = 5$) to the configuration found for $M = 10$ is just 0.02 for the quality Q due to a similar decrease of p_r. The effect of this is even clearer for the result shown in Figure 12. This figure show the step-wise results for the best feeder configuration the algorithm finds for the Brick part, allowing a max search depth of $M = 10$.

The result is similar to the feeder configuration for $M = 5$, but includes an extra *Step trap*, another $Er \rightarrow WB$ sequence and three extra *Wiper blades*. Although the solution is valid from the perspective of the algorithm there is actually very little improvement over configuration 3 previously listed in Table 2. This new configuration scores a $Q = 0.28$ (0.02 higher) due to a 0.01 decrease in p_r. Looking at Figure 12 and the consecutive three *Wiper blades*, only the first makes real changes to the probability distribution of the 24 orientations. This is also the case for the first

$Er \rightarrow WB$ sequence, where the impact of the second sequence is insignificant. Running this test with the dataset used in (Christiansen et al., 1996), confirms the validity of their result, but also shows that the before mentioned sequence of consecutive *Pressure break* traps have close to zero impact on the result after the fourth repetition of the trap.

5 DISCUSSION AND FUTURE WORK

The results presented in Section 4 show that the algorithm automatically finds feeder configurations that orients the three parts used as cases. The solutions found are optimal for the given input data, but the quality of these feeder configuration also relies completely on behavioural data. Finding better solutions for orienting the three parts would therefore require either the traps being tuned to optimal performance or more trap principles capable of reorienting the parts to other orientations. Regarding the latter, this could especially be an advantage for the Brick, which is well suited for orientation using the *Slotted track* trap, but has very little probability of entering that trap in the required input orientation for it to work.

The margin for considering a part fully oriented, m_c, should ideally be set to 1 (as discussed), but for the test it was set $m_c = 0.95$. This could potentially have resulted in the algorithm returning solutions with worse orienting capabilities (p_{CO} score), than the ones presented in Table 2, but scoring a higher quality due to lower p_r. Setting this parameter for the algorithm should therefore be governed by some knowledge on the optimality of the traps used in the search and the closer the traps are to being optimal the smaller the need will be for decreasing m_c.

In Section 4.4 it was shown that the algorithm uses time exploring branches of the solution tree that offers improvement of insignificant magnitude. This is to be expected and dealing with this appropriately would lead to further reduction in search times. A simple way of doing this could be to impose a lower bound for changes in quality, but that raises the question of where the threshold for significant improvement lies. In the future we intend to explore this problem further and pursue improving the algorithm by looking for heuristics guiding the search towards good feeder configurations faster, as well other, more aggressive, branch termination strategies.

In the current state our method for generating data is unable to identify stacking parts. This is a problem occurring frequently in this type of feeding system and should be taken into account when designing the feeder. This becomes and issue as our method assumes that parts are singulated when generating data and therefore only simulated one part interacting with the trap at a given time. Simulating just a single part in the feeder also does not model the effects of parts pushing on each other, potentially introducing parts being conveyed in other orientations than expected. Future work should be directed at efficiently simulating multiple parts interacting with each other as well as the feeder.

Finally we are in the process of validating the designs found using the algorithm with real world tests.

6 CONCLUSION

In this paper we have outlined a framework for automatic design of vibratory feeders and presented concrete methods for automatically encoding behavioural data and the subsequently selection and sequencing of traps for orienting parts in a vibratory parts feeder. The behavioural data are generated using dynamic simulation and encoded into transition matrices known from prior literature. The selection and sequencing method is an informed search strategy that efficiently reduces the computation time making the otherwise hard combinatorial problem manageable. To test the presented methods nine different trap types have been implemented and behavioural data generated for three different parts together with an analysis on how many samples are required for a stable estimate of the transition matrices. The resulting designs has been further analysed and properties of the solutions are discussed.

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