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Crowdsourcing solutions to 2D irregular strip packing problems from Internet workers

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Many industrial processes require the nesting of 2D profiles prior to the cutting, or stamping, of components from raw sheet material. Despite decades of sustained academic effort, algorithmic solutions are still sub-optimal and produce results that can frequently be improved by manual inspection. However, the Internet offers the prospect of novel ‘human-in-the-loop’ approaches to nesting problems that uses online workers to produce packing efficiencies beyond the reach of current CAM packages. To investigate the feasibility of such an approach, this paper reports on the speed and efficiency of online workers engaged in the interactive nesting of six standard benchmark data-sets. To ensure the results accurately characterise the diverse educational and social backgrounds of the many different labour forces available online, the study has been conducted with subjects based in both Indian IT service (i.e. Rural BPOs) centres and a network of homeworkers in Northern Scotland. The results (i.e. time and packing efficiency) of the human workers are contrasted with both the baseline performance of a commercial CAM package and recent research results. The paper concludes that online workers could consistently achieve packing efficiencies roughly 4% higher than the commercial based-line established by the project. Beyond characterising the abilities of online workers to nest components, the results also make a contribution to the development of algorithmic solutions by reporting new solutions to the benchmark problems and demonstrating methods for assessing the packing strategy employed by the best workers.

Keywords: crowdsourcing; two-dimensional strip packing problem (2SP); Internet worker; packing efficiency; component nesting

1. Introduction

For many of the combinatorial problems found in manufacturing and design (e.g. job shop scheduling, route planning or container packing), there is no guarantee that an optimum solution will be found with today’s engineering software (Harman 2007). So, instead of perfect solutions, ‘good’ ones are computed and consequently it is frequently possible for humans to improve on algorithmically generated results (Syberfeldt et al. 2015). The generation of nested layouts is typical of such problems and has been extensively studied because of the numerous industrial applications where there is a need to place a number of arbitrary shapes into the smallest possible area. For example, in the manufacture of sheet metal stampings, material can represent 75%, or more, of the total cost; consequently, even small changes in material usage can directly impact on the profits of an enterprise (Rao 2007). Similar economic considerations exist in the wood, leather, clothing, glass and paper industries, where 2D shapes have to be cut from large sheets of raw material. In all cases, the aim is to reduce the cost by minimising the amount of material left after the desired shapes have been cut out.

Because of the industrial importance of packing problems, many algorithms and improvements to existing strategies have been proposed (Dowland and Dowland 1995; Lodi, Martello, and Monaci 2002; Riff, Bonnaire, and Neveu 2009). Most of these approaches apply different computational methodologies for searching the ‘space’ of all the possible layouts for the ‘best’ ones. However, regardless of their sophistication, such software only rarely produces optimum arrangements because of the potentially vast number of possible solutions and the frequent use of general heuristics (e.g. arrange the largest components first) to guide the search. Furthermore, although a shape in a nesting problem could potentially have any orientation, or position, many commercial algorithms only explore a discrete (i.e. fixed) number of component orientations (e.g. 90°, 180°, 270°, etc.). Such strategy is effective in reducing the size of the search space but also inevitably results in sub-optimum solutions.

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Indeed, given that packing problems are known to be NP-hard (Lodi, Martello, and Vigo 2002), it is arguable if truly optimum solutions can ever be computed for anything but trivial cases. So, while academic work on the many variants of the ‘packing problem’ continues to provide algorithms that provide ever closer approximations to an ‘optimum solution’, there is still room for innovation. Given this context, this paper presents the results of a series of trials conducted as part of a larger investigation into the capability of online workers to improve the solutions of geometric optimisation problems found in CAM applications. The investigation of two-dimensional strip packing problems (2SP) (using online workers both in India and Scotland) has been used as a specific example of this general class of tasks.

The research is motivated by the observation that the human ability to interpret and reason about shapes is frequently impressive and is often difficult to reproduce algorithmically. However, only recently has it become possible to access human problem-solving capabilities as an online service available 24/7; this emergent technology raises the possibility that a ‘human-in-the-loop’ approach could be exploited in many computationally difficult industrial problems to improve productivity or quality. Research into other crowdsourcing applications (in areas such as image identification, language translation and design, etc.) has identified that the online user interface to the task and ability to quantify the quality of results is a crucial factor in any job being presented to a distributed workforce. Since this research aims to establish the potential benefits of using online workers for CAM optimisation tasks, the following research questions are addressed:

- (1) How should the task be presented to an online worker to produce the best result?
- (2) How do the solutions produced by online workers compare to those generated by commercial and academic software?
- (3) What is the time and cost of solutions generated by the online workers?
- (4) Is it possible to identify the packing strategies employed by online workers to achieve higher efficiency?

To answer these questions, an online platform for CrowdPowered CAM was developed to enable systematic investigation of ‘2D Irregular Strip Packing (2SP)’ problems. Although an open, public crowdsourcing site was used to develop the system’s user interface, the need to guarantee the security of commercial data mandated the use of a closed, private network of online workers for the subsequent quantitative study of human performance.

The rest of the paper is organised as follows. Section 2 reviews the literature on the two-dimensional nesting. Section 3 details the research questions, methodology and experimental the platform developed to enable the investigation. Section 4 reports an initial scoping study using a public (open) crowdsourcing site to assess the relative effectiveness of three different ways of presenting a 2SP task to workers. Section 5 compares performances of private (closed) crowds of online workers in India and Scotland, with the results of commercial and academic nesting software. Section 6 details the investigation of packing strategies employed by the online workers. Section 7 summarises and discusses the findings. Finally, Section 8 draws conclusions and describes future work.

2. Two-dimensional packing problem overview

The academic study of packing has given rise to numerous sub-problems (i.e. special cases of the general problem), each of which is associated with particular industrial applications. Broadly speaking, packing problems can be classified as one-, two- or three-dimensional problems, depending on the number of spatial dimensions available to the process. In the case of two dimensions, the packing problem can be classified in two general groups (Lodi, Martello, and Vigo 2002):

- (1) The two-dimensional bin packing problem (2BP), in which a list of 2D shapes and an unlimited number of identical 2D rectangular ‘bins’ are given with the objective of packing all the 2D items, without overlap, using the minimum number of containers.
- (2) The 2SP, in which, a list of 2D shapes and a 2D strip (with fixed width and infinite length) are given with the objective of packing all the given items, without overlapping, using the minimum length of the strip.

The algorithms reported for these 2BP and 2SP can also be broadly classified into two groups known, respectively, as online and offline (Miyazawa and Wakabayashi 2003). Essentially, online algorithms are analogous to the game Tetris; items have to be packed in the order given by the list; each item is packed without knowledge of any item remaining in the packing list, and are not allowed to move once packed. In contrast, offline algorithms have knowledge of all the parts to be packed and are able to relocate parts many times during their search for the best (or at least a good) solution.

Much of the literature on two-dimensional packing is dominated by so-called ‘regular packing’ problems, where regular rectangular boxes are packed into bins or strips. Furthermore, in most of these algorithms, rotation of shapes from the orientation given in the list is either not allowed or limited to a number of discrete angles (e.g. 45°, 90° and 180°).

Some examples of these algorithms are the online parametric algorithms for packing rectangles and boxes (Miyazawa and Wakabayashi 2003), genetic algorithms for 2BP (Hooper and Turton 1999; Kröger 1995), two-level search algorithms (Chen and Huang 2007), evolutionary particle swarm optimisation algorithm (Omar and Ramakrishnan 2013), dynamic programming and column generation-based algorithms with rectangular shapes and orthogonal rotations of items (Cintra et al. 2008; Liu, Chu, and Wu 2014) and hybrid algorithms (Soke and Bingul 2006). Although fewer algorithms related to 2D irregular packing (i.e. nesting) problems have been reported in the literature, it is a common task in many industrial applications where a given set of non-convex polygons must be placed, without overlap, within a rectangular container having a fixed width and a variable length (Figure 1). Some examples of the approaches proposed in the literature to solve the irregular strip packing (2SP) problem are: the local search algorithm for overlap minimisation (Umetani et al. 2009), a semi-discrete representation of irregular geometric shapes (Akunuru and Babu 2013), heuristic approaches (Gomes and Oliveira 2002), metaheuristic approaches such as Simulated Annealing and Tabu search (Dowland and Dowland 1995), object-based evolutionary algorithm (De Armas et al. 2010; Ratanapan, Dagli, and Grasman 2007) and hybrid algorithms combining metaheuristic and linear programming (Gomes and Oliveira 2006; Wu et al. 2003).

The algorithms related to the 2D packing problems in general have been classified into heuristic, metaheuristic and hybrid approaches (Lodi, Martello, and Vigo 2002; Riff, Bonnaire, and Neveu 2009). In terms of quality of solution/performance, the hybrid algorithms offer the best performance (Gomes and Oliveira 2006; Hooper and Turton 2001), but their execution times are high and become larger with increasing problem size. Metaheuristic algorithms are better in terms of execution times and generally yield results which are only slightly worse than hybrid methods. However, when only limited time is available, heuristic methods must be employed (Hooper and Turton 2001).

To allow easy comparison of the performance of different algorithms, researchers have established benchmark data-sets (EURO ESICUP 2009) against which quantitative assessments of packing efficiency and time can be made. For example, the progress of algorithms developed for solving 2SP problem using the Albano data-set (Albano and Sapuppo 1980) over the past decade is illustrated in Figure 2. The figure shows that it has taken almost a decade of research to produce a 3% increase in Albano packing efficiency. Although the algorithmic solutions are maturing, none of the algorithms consistently produces best performance across all 2SP problems and their associated benchmark data-sets. This variability clearly demonstrates the uncertainty involved in algorithmic solutions, and the difficulty of generating a consistent quality of 2SP solution.

Although there is clear progress in algorithmic performance, the transfer of this knowledge from academic labs to shop floor CAM systems is an issue. To illustrate this problem, the authors tested a set of academic benchmark data-sets for 2SP problems with commercially available software. Commercial confidentiality prevents identification of the system used; however, it is an established product (over 10 years old) that is sold as component software and incorporated in several well-known CAD/CAM systems with many hundreds of thousands of installed seats. Figure 3 plots the packing efficiency score achieved by the commercial software (in both the ‘fast’ and ‘optimum’ settings) against recent academic results (Elkeran 2013). The figure shows that the best packing efficiency reported in the academic literature is much higher than the commercial result for all but one of the tested benchmark data-sets (i.e. the Swim data-set). On average, the commercial CAM system was around 10% below the reported results and in one case (Shapes 2), over 20% worse. Although not a systematic study of all available commercial systems, the results demonstrate that there is a significant delay between algorithmic solutions arising from academia reaching industrial application. These commercial baseline and recent research results will be used to assess the performance of online workers in later sections of the paper.

Given the theoretical limitations of reported algorithms and the practical ‘knowledge-transfer-lag’ of commercial application, there is an opportunity to use online workers to significantly improve the packing efficiencies available to industry today. Given that the task of forming a cutting plan, by laying out component profiles onto stock-sheets, has long been done manually by factory workers, there is little doubt that humans are capable of generating good solutions.

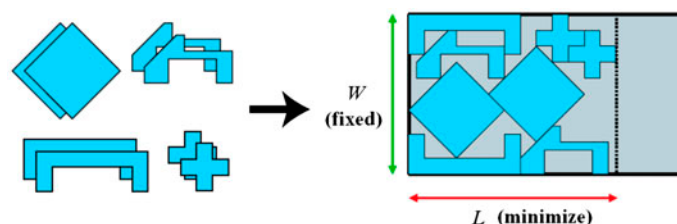


Figure 1. The irregular strip packing problem (2SP).

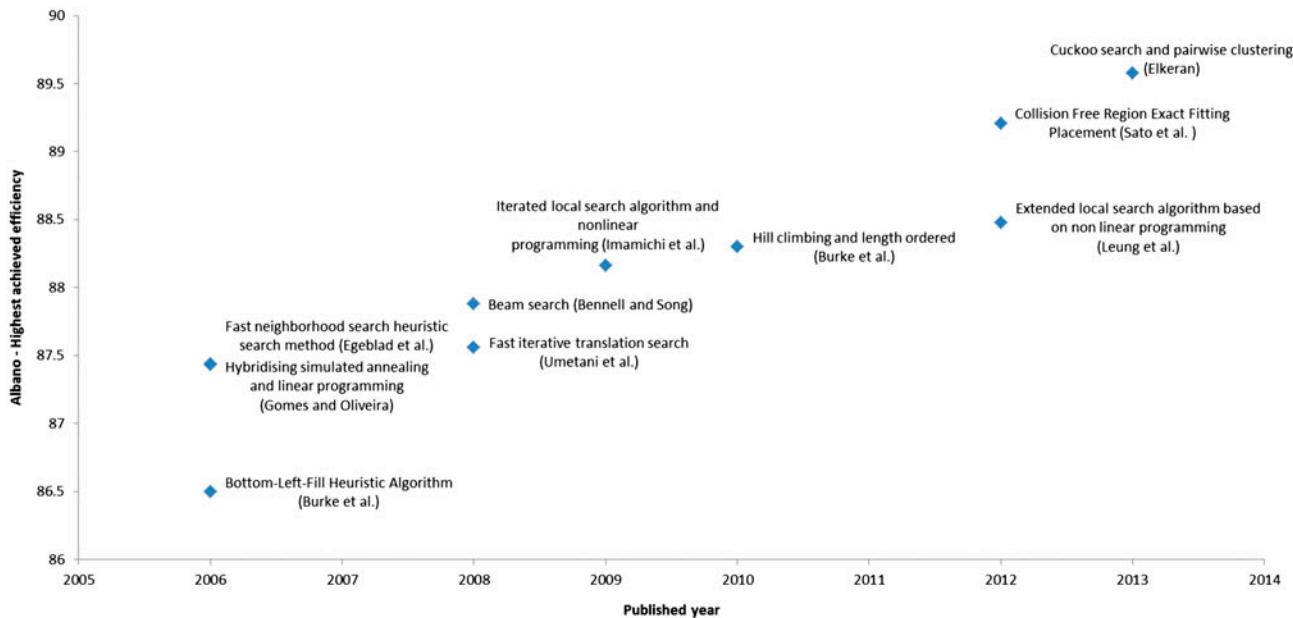


Figure 2. Reported 2SP performance between 2005 and 2014.

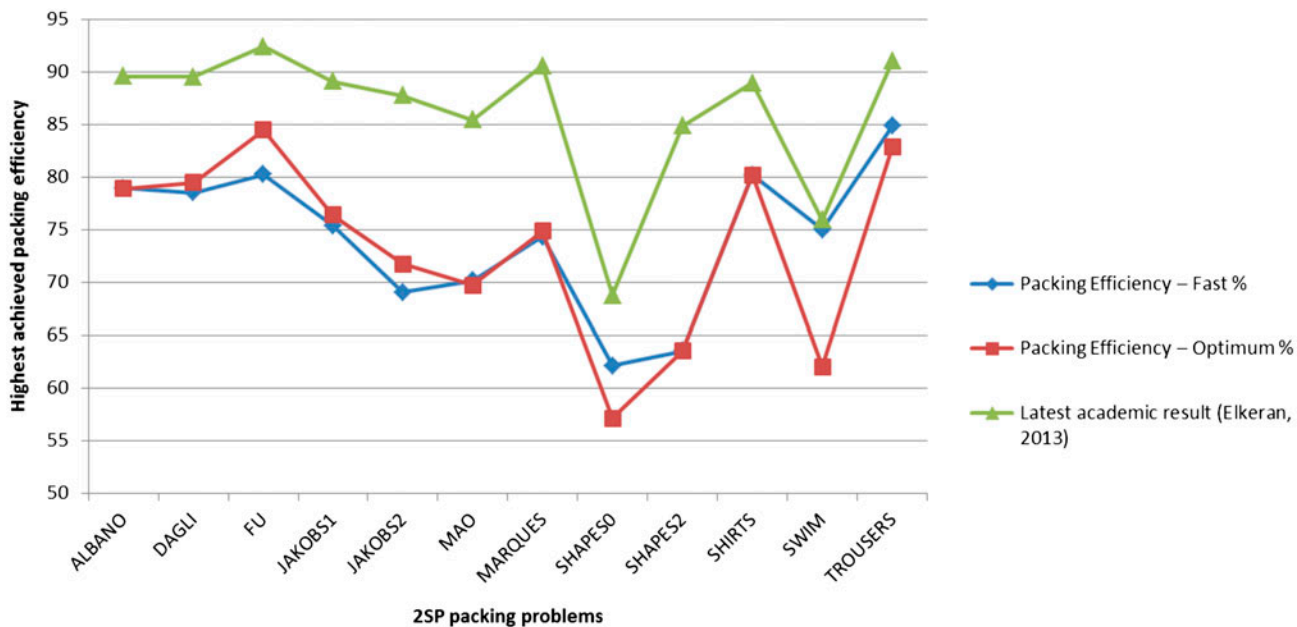


Figure 3. Nesting efficiency achieved by commercial and academic systems.

What is unclear, however, is how well an online workforce could do the job in comparison to algorithmic approaches and how long it would take them. The following section details the approaches formulated to answer this research question.

3. Research questions, methodology and experimental platform

The following research questions are discussed in subsequent sub-sections and aim to both assess performance and develop insights into the processes used.

- Q1. How should the 2SP task be presented to an on-line worker to produce the best result?
- Q2. How do the solutions produced by on-line workers compare to those generated by commercial and academic software?
- Q3. What is the time and cost of solutions generated by the on-line workers?
- Q4. Is it possible to identify the packing strategies employed by on-line workers to achieve higher efficiency?

Given the need for data security, questions 2 and 3 must be investigated using a private, or closed, crowd who can ensure commercial manufacturing information is not publically displayed. However, the interface development and testing (i.e. Q1) can be done on an open public crowdsourcing site.

3.1 A user interface for 2SP problems

The first question to be answered is ‘how should the 2SP task be presented to an on-line worker to produce the best result?’ Other investigations of crowdsourced applications have reported that results generated by the workers will be significantly influenced by how the task is presented to them (Alonso and Baeza-Yates 2011). After a review of the literature, three different presentation approaches were framed for the 2SP task, namely: 2SP-Blind, 2SP-Text Maximum and 2SP-Picture Maximum. Essentially, the presentation approaches differ in terms of the amount of information obtained about the best previously obtained efficiency score, displayed to the workers. These alternative interface designs were motivated by evidence in the literature that human intelligence tasks which allow incremental improvement of results produce better results (TurKit 2010). Two benchmark data-sets downloaded from the ESICUP website (EURO ESICUP 2009) known as Albano and Jakobs1 (Albano and Sapuppo 1980; Oliveira, Gomes, and Ferreira 2000) were used to experimentally assess the performance of the three different interfaces. Originating in the textile industry, the Albano data-set comprises 24 items and the Jakobs1 data-set comprises 25 items. The three approaches presenting tasks to the online workers can be summarised as:

- (1) 2SP-Blind: In this presentation, no previous best solution to the problem was shown to workers. So, workers started without any knowledge of the expected level of performance.
- (2) 2SP-Text Maximum: In this task presentation, each worker was allowed to see the best previous value of packing efficiency achieved (e.g. 73%), only as a numerical value.
- (3) 2SP-Picture Maximum: Similar to ‘Text Maximum’, but this time, the worker was allowed to see the best previous packing arrangement achieved, as a picture of the layout along with a numerical value (e.g. 73%).

Amazon’s Mechanical Turk (commonly referred as ‘mTurk’) was used as a crowdsourcing platform to conduct the trials of the different possible user interfaces. This well-known platform enables employers to post jobs on the mTurk website with set monetary payment and workers (who are potentially anyone with an Amazon account) to search and select jobs. Once completed, payment is credited to their Amazon accounts (see www.mturk.com). Using the mTurk application programming interface, a CrowdPowered CAM system known as ‘cNest’ was designed and implemented (Figure 4). The system presents workers with a set of 2D shapes which had to be packed within a defined rectangular area using the minimum overall length. The system interface provides the following functionality:

- (1) Shapes can be moved and rotated to any position.
- (2) Shapes can be roughly and finely (i.e. nudged) moved or rotated.
- (3) Colours are used to identify items (green), free space (white), bounding area (red) and overlaps (e.g. clash or interfere) among items or the boundary (brown).
- (4) The display could be zoomed in and out to allow precise positioning.
- (5) The overall length of the packed shapes is dynamically calculated and displayed.
- (6) The packing efficiency (i.e. the percentage of used area with reference to occupied overall length and given width) is dynamically calculated and displayed.
- (7) The optional facility to display the best previously generated packing arrangement as either an efficiency % value or an efficiency value plus a picture.
- (8) Recording of the working time between the movement of the first shape and submission.
- (9) A voluntary questionnaire for workers that requests gender, age, education, country and experience of providers.

Closely pack the shapes/parts (Please use Microsoft Internet Explorer with latest version of Flash installed)

- * This task is to pack the green shapes on the right as tightly as possible in the Red bounding area.
- * This HIT requires that you use Internet Explorer with latest version of Flash installed.
- * The individual shapes can be moved and rotated to any positions.
- * Arrangements will be valid if no part of any of the green shapes lie outside the Red bounding area and no green shapes overlap (e.g. clash or interfere) with each other or the red boundary.
- * Details of the key strokes and mouse button actions used to position shapes are given to the left of the HIT.
- * The efficiency of packing will be indicated below the Red boundary.
- * Shapes that overlap either the boundary or other green shapes will be indicated by a change of colour. Note that sometimes the system will highlight a clash (i.e. interference or overlap between shapes even when there is still a visible gap between them. This is caused by combination aliasing and pixel resolution effects. In ALL cases shapes should be sufficiently far apart to prevent ANY system detected overlaps. Even when visually it appears they could be slightly closer.
- * HITS will be rejected where there has been little effort to minimise the packed area or where overlaps are detected by the system. Please understand the task is NOT to evenly spread the green shapes across the Red bounding area and press the submit button! The job is to get these parts into the smallest possible rectangular area.
- * Shape moving/rotating could be slow. So please take your time and patience

Answer the questions about yourself (this is for academic research and will not be used to judge the quality of the work).

Gender Age Average time per week spend on MTurk education Country

Experience Yes No

I have experience of mechanical engineering or manufacturing

I have experience of using 3D CAD or Computer Graphics

I have experience of using maths for analysis

Experience of playing video games like Tetris

CONTROLS

use mouse to drag and move shapes

R - rotate clockwise

shift + R - rotate anti-clockwise

N - nudge rotate clockwise

shift + N - nudge rotate anti-clockwise

left arrow - nudge left move


right arrow - nudge right move

up arrow - nudge up move

down arrow - nudge down move

NOTE: nudge moves are very minute

PACKING AREA



start moving shapes into packing area

Number of shapes in bounding area:

SHAPES

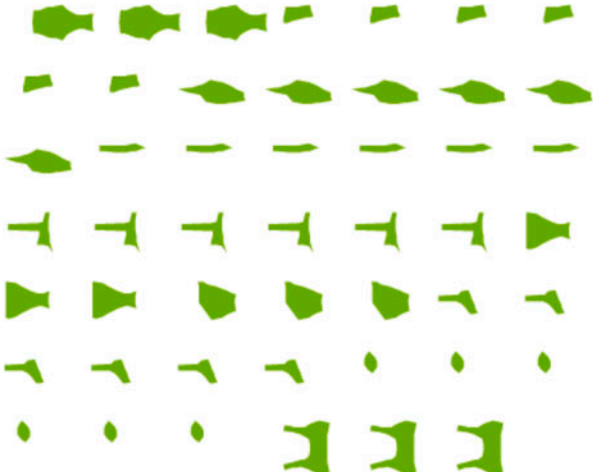


Figure 4. The mTurk CrowdPowered 2SP interface (cNest).

The cNest programme was used to conduct trials of the three presentations for the Albano and Jakobs1 benchmark data-sets.

3.2 Methodology for research questions 2 and 3

The research questions 2 and 3 aim to quantify the performance of the available online workers (regardless of their educational or social background) by testing their problem-solving skills using six 2SP benchmark problems. To support this study using a private network of workers, a crowdsourcing platform (known as the CrowdCAM platform) was created with the functionality detailed in Figure 5.

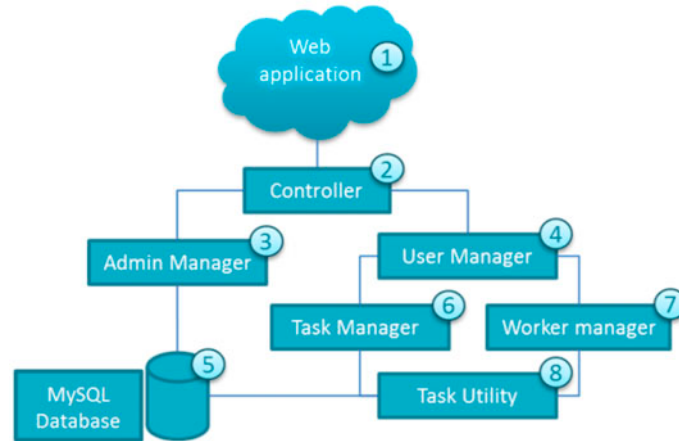


Figure 5. Schematic architecture of the CrowdCAM platform.

The experimental platform was implemented as a web application designed using a combination of PHP, HTML, JavaScript, JQuery, CSS, MySQL and X3D (open-source 2D/3D object visualisation tool). The web application has a controller, admin manger, user manger, task manger, worker manger and task utility components and was deployed using Amazon Web Services (AWS). Each worker registered and their information was stored in a secured MySQL database (provided by AWS). The 2D packing tasks were hosted by an Ubuntu webserver (provided by AWS).

The cNest interface illustrated in Section 3.1 (Figure 4) was delivered via this platform. In addition to the functionalities listed, the platform also automatically recorded log of each user's action (e.g. nudge, rotate, zoom, etc.) as they worked on a nesting task. The recorded actions are classified into six packing moves, namely: Movements, Nudge movements, Rotation, Nudge rotation, Flip and Manual entry. These records enable the investigation of the fourth research question (i.e. relationship between the actions of online workers and the packing efficiency they achieved). The data allowed investigation of both simple numerical comparisons and more complex relationships between shape size and placements. Two examples of numerical comparisons are presented that test the hypotheses: (i) the highest packing score will correlate with the number of packing moves (Movements, Nudge movements, Rotation, Nudge rotation, Flip and Manual entry); and (ii) the highest packing score will correlate with the time taken to solve the problem.

Beyond these numerical correlations, a number of possible heuristic packing strategies were tested against the recorded data. The aim of this analysis is to see if the approach (i.e. strategy) employed by the best human worker could be identified. The platform was rigorously tested before starting the experimental trails. The platform has a merit of confidentiality which is lacking when using public crowdsourcing platforms such as mTurk. Using the CrowdCAM platform, experiments were conducted with 40 workers employed in two business process outsourcing (BPO) centres in rural India and 28 rural homeworkers in the north of Scotland. To motivate the workers to achieve the best packing efficiency scores, the Scottish homeworkers were offered a bonus of £1 for every task in which they produced a better score than the given benchmark reference efficiency. This bonus was on top of £6.50/h received for their participation. For Indian BPOs, to increase competitiveness among workers (who were sitting together and undertaking the tasks in-parallel), the bonus scheme adopted offered the top 10 overall best performers a monetary gift (with higher payments for top ranks). The results collected from these trails are detailed in the subsequent sections.

4. Results: assessment results of alternative task presentation approaches

Gender and educational levels of the mTurk workers employed are reported in Table 2. The workers were mostly from USA (58%), followed by India (32%), Greece (6%) and Brazil (4%). Although mTurk is a global crowdsourcing platform where labour could potentially be located anywhere, a higher percentage of American workers were expected, given the origins and ownership of the site being used. Many had previous experience in areas related to nesting problems, for example, 76% had experience in playing games like Tetris, 66% in using maths for analysis, 31% in using CAD or graphics and 11% in mechanical engineering. Overall, the average worker was a young American male between 20 and 25 years old who spends about 8 h a week on mTurk and has experience of playing games like Tetris.

Three presentations for two different 2SP problems (Albano and Jakobs1) were posted on the mTurk site and 64 responses were accepted over a 50-h period. The responses were accepted only if the nesting problem was completely

Table 1. Results of the alternative presentation assessments.

Interface	Problem	Number of accepted responses	Efficiency (%)		Working time		Best outcome from a commercial software		Efficiency improvement (%)		Best academic results (Elkeran 2013)
			Best	Average	Time for the best solution (hh:mm:ss)	Average (hh:mm:ss)	Efficiency (%)	Average time (hh:mm:ss)	Best	Average	
Blind	<i>Albano</i>	10	87.92	80.15	01:27:35	00:49:10	78.96	00:10:39	8.96	1.19	89.58
Text	<i>Albano</i>	17	89.41	83.57	01:06:58	00:58:42			10.45	4.61	
Picture	<i>Albano</i>	6	90.43	84.33	00:29:06	00:54:24			11.47	5.37	
Blind	<i>Jakobs1</i>	10	79.17	70.47	00:48:17	01:22:13	76.39	00:03:27	2.78	5.92	89.1
Text	<i>Jakobs1</i>	12	80.72	71.36	00:49:02	01:07:02			4.33	5.03	
Picture	<i>Jakobs1</i>	9	82.21	72.14	00:58:39	01:10:05			5.82	4.25	

Note: Bold letters signify better packing efficiency achieved with the 2SP-Picture interface for both problems.

solved (i.e. all shapes were placed within the packing container without overlap). No worker was allowed to repeat the task with different presentation approaches. Table 1 summarises the results obtained with three presentation approaches for each 2SP problem. This table also presents the packing efficiencies obtained from a commercial system and reported by academic researchers.

For both data-sets, the 2SP-Picture interface produced the best overall results. For the Albano problem, it was higher than the 2SP-Text by 1.02% and the 2SP-Blind by 2.51%, and for the Jakobs problem, it was higher than the 2SP-Text by 1.49% and the 2SP-Blind by 3.04%. The best overall result for the Albano problem produced by an mTurk worker was 90.43% efficiency (compared to the best result obtained from the commercial software benchmark of 78.96%, showing an improvement of 11.47%). In the case of Jakobs1 data-set, the best overall result was 82.21% efficiency (compared to the best result obtained from commercial software 76.39%, an improvement of 5.82%). Having established an effective interactive system for 2D packing tasks, the focus of the study moved to assess the abilities of private networks of workers across a larger range of data-sets.

5. Performances of online workers in India and Scotland

5.1 Background of rural BPO workers and homeworkers

There are many providers of online labour for work that can be characterised generally as ‘micro-outsourcing’ (the execution of small tasks in return for a one-off payment). These service providers range from large public operations (e.g. Amazon’s mTurk), which are open to almost anyone to undertake any task, to providers of private crowds (e.g. www.crowdfunder.com) specifically assembled for a particular task. Although the open sources are useful for quickly testing user interfaces and putting bounds on the likely performance, any commercial organisation would need to ensure the security of its client’s data and so, closed crowds (whose identify and backgrounds are known) are employed to do tasks like content moderation for social media sites. The closed crowds are implemented either by the worker concentrated in IT service centres (e.g. Business Process Outsources, aka BPOs) or curated (e.g. registered and approved) networks of homeworkers.

To assess the capabilities of closed networks, we selected two rural BPO centres located in different states of India (one each from South and North India, Figure 6(a)). The centres are representative of over an estimated 500 similar enterprises in India providing global services ranging from text entry to customer contact. Researchers agreed to anonymity for these commercial operations and so the exact locations of these centres are not presented. Since these tests were conducted in a real-time business environment, the choice of rural workers to participate in the study was controlled by the BPO centre. Twenty rural workers participated in each rural BPO centre. Overall, this paper reports the analysed results of 40 rural BPO workers. Table 2 and Figures 7(a) and 7(b) present the background information about the participants of both the centres. The participants in Centre 1 were dominated by females (70%), mostly experienced IT workers with more than 2.5 years of experience (65%), young (65% under 30 years old) and equally distributed between school passouts and college graduates. In contrast, the participants in Centre 2 were dominated by males



Figure 6(a). Locations of chosen two rural BPO centres (centre ID provided).

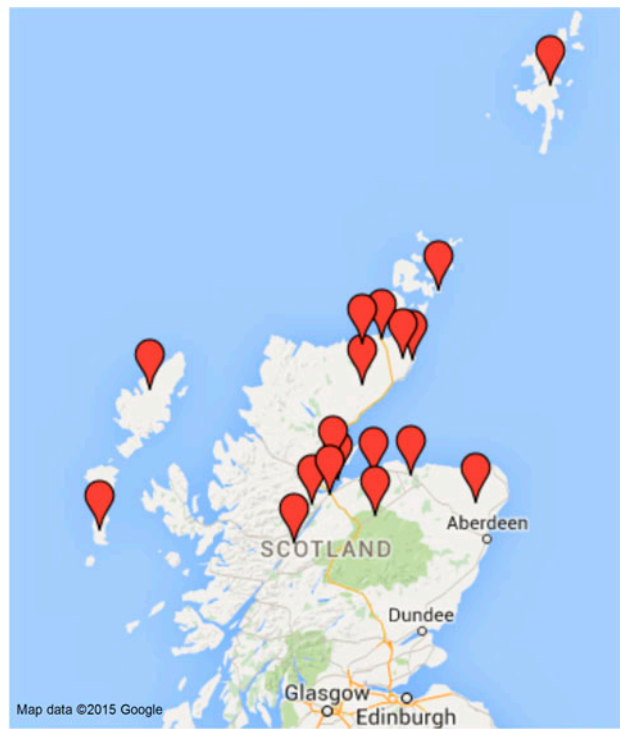


Figure 6(b). Locations of participated rural Scotland homeworkers.

Table 2. Background of the participated workers (only for those who provided these details).

Variables	mTurk workers	India rural BPO centres		Scotland homeworkers
		Centre 1	Centre 2	
Count				
School passouts	5	9	14	11
Graduates	20	11	6	15
Male	15	6	14	10
Female	10	14	6	16

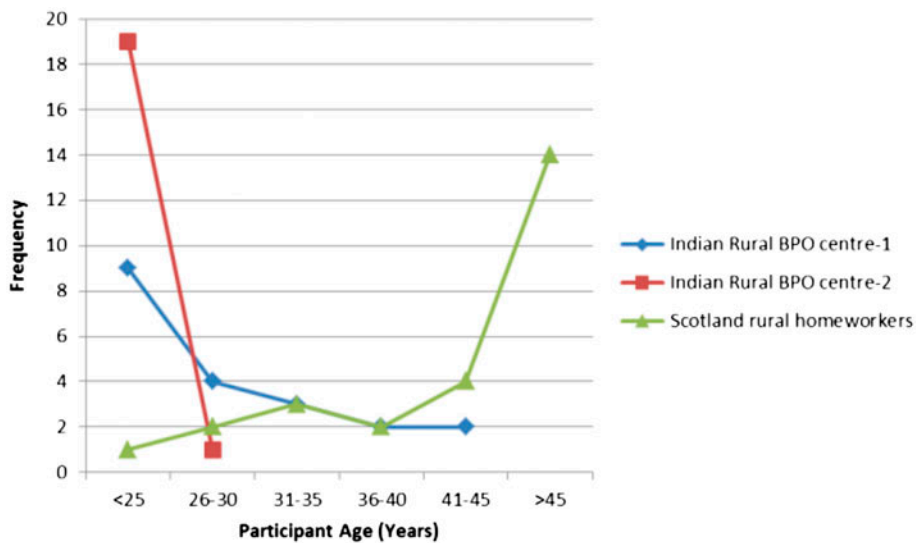


Figure 7(a). Age of participants.

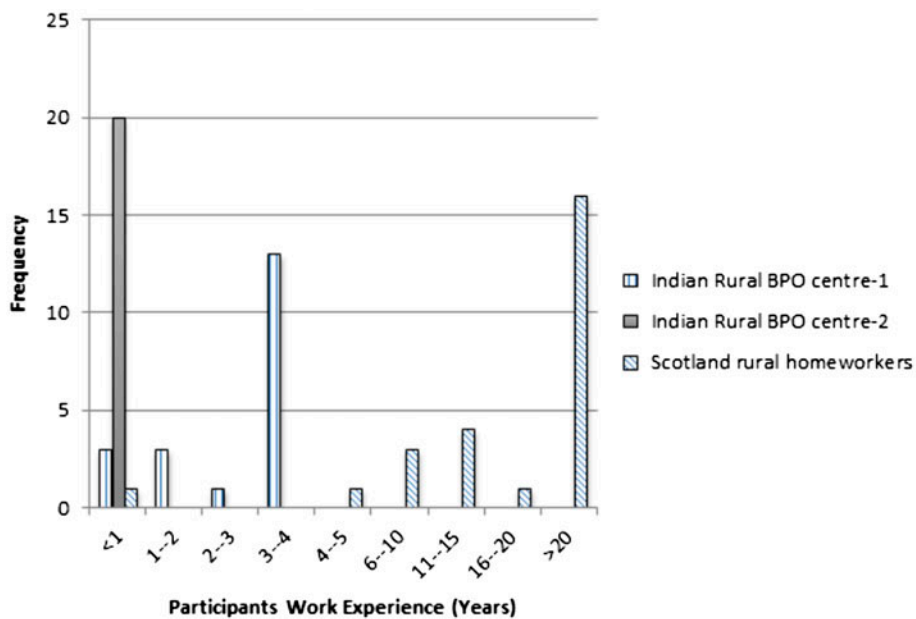


Figure 7(b). Work experience frequency distribution of participants.

(70%), all of them were relatively inexperienced IT workers, mostly young (95% under 25 years old) with higher percentage of school passouts (70%) than graduates. These variations resulted from the fact that Centre 2 was newly established in comparison to Centre 1.

To ensure that the study covered the entire spectrum of online workers, the researchers also investigated the capabilities of rural homeworkers in a developed economy. Since High-Speed Broadband is widely available in the Scottish Highland, rural Internet-based homeworkers were chosen as being representative of this population. Through advertisements in rural newspapers and community websites, 28 homeworkers were recruited (Figure 6(b) maps the participants' locations). The participants were based in locations across Scotland from Shetland and Lewis to South Uist. The background details of the participants are tabulated in Table 2 and Figures 7(a) and 7(b). Out of the 28 participants, only 26 filled the socio-economic survey. The participants in Scotland's homeworkers were dominated by females (62%), almost all are highly experienced (with the exception of one worker), middle-aged people (88% are >30 years) and mostly graduates (58%) than school passouts. Age and work experience are the major differences between the Indian rural BPO workers and Scotland homeworkers. The experiments were conducted by providing an image of the 'best' nesting layout generated by a leading commercial CAM system for each of the benchmark packing problem. The commercial nesting system used is incorporated in several popular CAD/CAM systems and is therefore indicative of current capabilities in this area. The subsequent sub-sections discuss the results in the context of the research questions described in Section 3.

5.2 2SP packing efficiencies produced by rural workers in India and Scotland

Table 3 presents the highest packing efficiency scores achieved by rural workers in India and Scotland when shown a target generated by a commercial CAM system. The results demonstrate that the rural workers in India and Scotland were able to achieve better results than the commercial software in all the six benchmark packing tasks. It can also be observed that in all the six packing tasks, the Scottish homeworkers achieved a higher packing efficiency score than either of the rural BPO centres in India (Figure 8), who both produced very similar scores. The maximum efficiency gain of 12.17% over the commercial CAM baseline was achieved in the 'Jakobs2' packing task by a Scottish worker. Even in 'Fu' task (with only 12 simple packing elements), the workers were able to achieve 4.6% improvement over the commercial CAM baseline.

Scottish homeworkers took less time to complete all the six packing tasks (on average 43 min) than Indian rural BPO workers (on average, Centre 1: 01h49 m; Centre 2: 01h45 m). However, in all cases, the time taken for the workers to produce solutions is much higher than the commercial CAM software. Table 4 reports the number of workers who achieved higher efficiency over the given commercial baseline. For each of the tasks, between 40 and 68% of the Scottish homeworkers earned bonus by achieving the higher efficiency. But the spread of ability is much wider for the Indian BPO workers (10–85%). This variation demonstrates that the Scottish homeworkers are more consistent in achieving a better packing efficiency than the Indian BPO workers.

Table 3. Highest packing efficiency scores achieved by rural workers in India and Scotland.

Packing tasks	Indian rural BPO workers				Scottish homeworkers		Commercial baseline		Best efficiency Improvement from Commercial Baseline (%)	Best academic results (Elkeran 2013)
	Centre 1		Centre 2		Best efficiency	Time taken (hh:mm:ss)	Best efficiency	Time taken (hh:mm:ss)		
	Best efficiency	Time taken (hh:mm:ss)	Best efficiency	Time taken (hh:mm:ss)						
Albano	81.06	01:43:19	82.91	02:36:48	86.54	01:30:30	78.96	00:10:39	7.58	89.58
Dagli	80.7	03:38:18	80.06	00:59:26	87.65	02:32:10	79.49	00:03:04	8.16	89.51
Fu	87.01	01:26:14	86.36	02:04:24	89.05	00:58:23	84.45	00:20:55	4.6	92.41
Jakobs1	80.72	01:01:07	80.82	01:43:27	88.08	00:49:36	76.39	00:03:27	11.69	89.1
Jakobs2	75.2	01:44:14	77	02:54:55	83.92	02:13:58	71.75	00:18:41	12.17	87.73
Mao	77.58	01:19:21	76.77	00:38:01	80.99	02:20:24	70.14	00:02:52	10.85	85.44

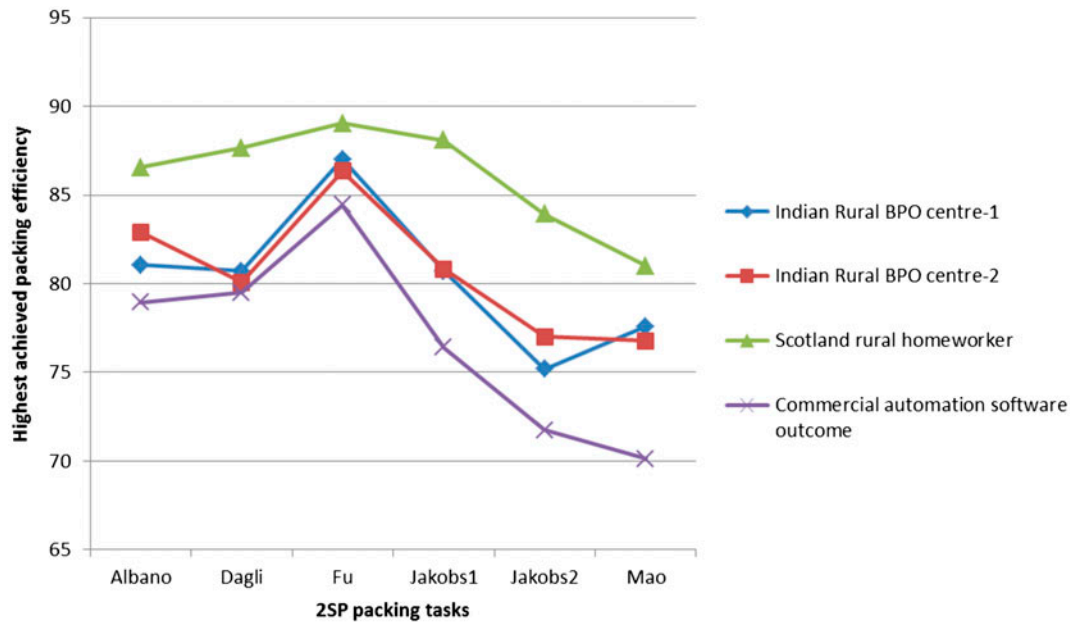


Figure 8. Comparison of highest packing efficiency with various modes of operations.

Table 4. Number of workers achieving higher efficiency than the given baseline.

2SP tasks	Scottish homeworkers	Indian BPO Centre 1	Indian BPO Centre 2
Albano	19	13	12
Dagli	12	2	4
Fu	11	3	2
Jakobs1	12	5	4
Jakobs2	11	6	6
Mao	19	17	17

The average increase in packing efficiency across Indian rural BPO Centre 1, Centre 2 and Scottish homeworkers over the commercial CAM baseline is 3.5, 3.8 and 9.2%, respectively. Overall, the results suggest that the crowdsourcing solutions were an average of 4% better, but took 1–2 h longer than the commercial baseline.

6. Investigation of packing strategy

The manual packing software also logged every action of the user. This data can be used to analyse the strategies used by the workers to achieve high packing efficiency. The following sections present examples of two generic types of analysis carried out with this data. The first makes direct comparison between numerical values, and the second uses classifications of shape and locations to investigate the possibility of identifying more complex patterns of behaviour.

6.1 Numerical comparison

The actions of workers were investigated using numerical comparisons framed by two hypotheses:

- (1) The highest packing score will correlate with the number of packing moves (Movements, Nudge movements, Rotation, Nudge rotation, Flip and Manual entry).
- (2) The highest packing score will correlate with the time taken to solve the problem.

To validate these hypotheses, a linear regression study was conducted by representing the highest packing score as a function of the number of different packing moves and the time taken for each task. The linear regression established

that both the number of different packing moves and the total amount of time taken had some statistically significant correlations with the highest packing scores. Indeed, these two variables accounted for between 20.2 and 62.5% (R^2 values) of the ‘explained variability’ in highest packing score for each benchmark task (Table 5).

However, closer examination of Table 5 shows the variable ‘time taken’ is the only significant coefficient in the ‘Mao’ packing task. For most of the packing tasks, the statistical significance between the use of the movement variables ‘nudge movement’ and ‘flip’ is stronger than the ‘time taken’ variable. Indeed, the ‘flip’ movement (with a high positive unstandardised regression coefficient) appears to be more important than the ‘nudge movement’ (Table 5). These results suggest that those workers who have good spatial reasoning ability achieve high packing scores through ‘flipping’ (in either X - or Y -direction) and are spending time using ‘nudge’ movements to reduce gaps between components. It can also be observed that on average, the Scottish homeworkers used more flip movements/worker (71.1) than the Indian rural BPO workers (67.7 and 47 flip movements/worker for Centre 1 and Centre 2, respectively). The packing layouts generated by both workers and CAM system are shown in Figure 9. Interestingly, Figure 9 reveals that despite being shown a ‘best known layout’ at the start of the task, the workers actually generated very different solutions, and so appeared not to be biased or constrained in their search for compact layouts. This result is based on analysis of the worker’s performance when the ‘best known layout’ was displayed. Further testing is needed (with random layouts displayed to workers shown as starting solution) to generalise the claim.

6.2 Relative size and placement patterns

In addition to investigating which shape manipulation operations were most frequently employed in the production of the best layouts, the data can also be analysed for insights into the strategies employed to design the arrangements. This has been done by examining the data for correlations between packing efficiency and patterns of behaviour associated with specific strategies. Review of the literature suggested the following strategies might be components of a manual packing strategy:

Heuristic 1: Largest First: Locate the larger shapes early in the nesting process.

Heuristic 2: Left First: Build from left to right with shapes reducing in area.

Heuristic 3: Maximise Clusters Sizes: Create large sets of closely fitting shapes.

Heuristic 4: Ensure breadth of search: Maximise the search by ensuring that moves are not always incremental.

Table 5. Significant regression coefficient value for each packing task.

Packing task	R^2	F	Sig.	Significant coefficient(s)	B	SE_B	β
Albano	0.341	4.44	<0.0001	Nudge movement	.000	.000	-.292**
				Flip	.077	.032	.362**
Dagli	0.625	13.556	<0.0001	Movement	-.009	.003	-.427***
				Nudge movement	-.001	.000	-.798***
				Flip	.076	.025	.284***
Fu	0.202	2.136	0.053	Flip	.109	.044	.325**
Jakobs1	0.408	5.211	<0.0001	Nudge movement	.000	.000	-.520***
				Rotation	-.004	.002	-.381**
				Flip	.090	.043	.237**
Jakobs2	0.289	3.188	0.007	Nudge movement	.000	.000	-.332**
				Flip	.161	.064	.327**
Mao	0.306	3.53	0.003	Time taken	.001	.000	.551*
				Movement	-.012	.005	-.615**
				Nudge movement	.000	.000	-.411***

Note: R – multiple correlation coefficient; F – F -test value; Sig. – Statistical significance value; B – unstandardised regression coefficient; SE_B – Standard error of the coefficient; and β – standardised coefficient.

* $p < 0.01$; ** $p < 0.05$; *** $p < 0.005$.

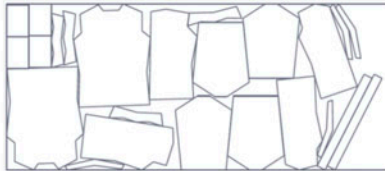
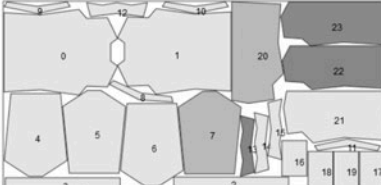
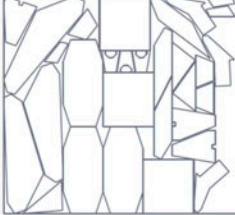
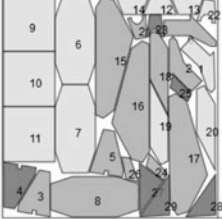
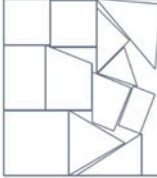
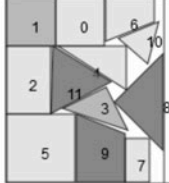

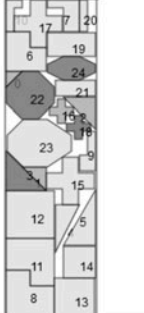

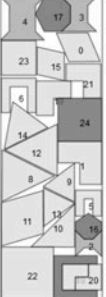


Packing tasks	Best commercial baseline outcomes	Best worker outcomes
Albano		
Dagli		
Fu		
Jakobs1		
Jakobs2		
Mao		

Figure 9. Layout comparison between best commercial and workers' outcomes.

To create a framework to investigate the above heuristics, the packing process was enumerated by: classification of shape (i.e. size), partitioning of locations (i.e. relative position in the packing area), quantification of space movement and cluster formation during nesting. The concept of clustering has been exploited by many researchers investigating 2D packing (e.g. Dighe and Jakiela 1996; Okano 2002). Essentially, a cluster is formed when two, or more, adjacent shapes have portions of their boundary that closely align. This allows the shapes to be closely positioned with only a nominal separation. Once formed, more shapes can be added to expand the number of objects in a cluster. However, frequently during packing, a cluster will grow to the point where none of the remaining shapes can be easily added to it. At this point, the cluster will have to be edited or modified. The concept of clusters is used in the following investigation to characterise the creation of tightly packed sets.

Considering each heuristic in turn:

H1: To enable the investigation of the worker's choice of which shapes to move, the shapes were divided into three roughly equal sets according to their area and labelled large, medium and small (Figure 10). This classification allowed the first heuristic (largest first) to be investigated.

H2: To study the relative placements of shapes, the bounding box of the average packing area was divided into three regions (defined in terms of the average overall length of the solutions generated by the workers). Figure 11 shows the classification of three regions. To ensure the placement of all shapes could be classified, the third region was allowed to be open ended (so the above average length solutions could be included). This classification allowed the second heuristic, Left First, (build from left to right with shapes reducing in area) to be investigated statistically.

H3: maximisation of cluster size was investigated by manually identifying the formation and modification of clusters through visual inspection of each worker's nesting process by replaying the step-by-step actions of each worker. In this way, the number of clusters created and broken during each nesting process was calculated. This allowed the relationship between cluster generation and packing efficiency to be investigated. A strong correlation would support the assertion that exploring many cluster options will result in identification of more compact arrangements of the shapes.

H4: The fourth heuristic (breadth of search) was assessed by quantifying the magnitude of shape moves: shape movement could be done between three regions of the bounding box or inside and outside the bounding box. These moves are illustrated by arrows in Figure 11.

To investigate to what extent the workers adopted these heuristics, a representative sample of packing moves were collected during workers' creation of a nesting layout for the Swim data-set by nine mTurk workers. The swim data-set comprises a relatively high number of 48 shapes (Figure 10). The complexity of the shapes in this data-set made it appropriate for the investigation. The following sections present the results of the analysis.

6.2.1 Heuristic 1: locate large shapes first

To assess the relationship between this strategy and the resulting packing efficiency, shapes were classified by sizes and the number of moves made by the workers calculated. The number of moves taken by the workers to reach a solution in this study varied from 590 to 1760. The percentiles of the total number of moves performed by all the users were used to normalise the range and visualise the frequency with which particular shapes were manipulated. The results of this analysis are plotted in Figure 12 and clearly show the workers' preference for handling large shapes during the early stages of the task, particularly in the first 10% of all movements. In contrast, medium shapes are predominantly handled in the latter half of the task. However, no clear tendency was observed in case of the small shapes; manipulation seems to happen with similar frequency throughout the whole task.

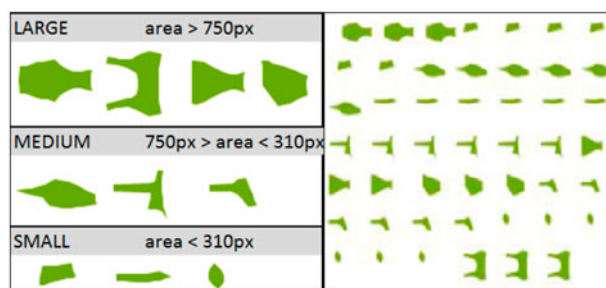


Figure 10. Shapes' visualisation for selection and classification of shapes by size.

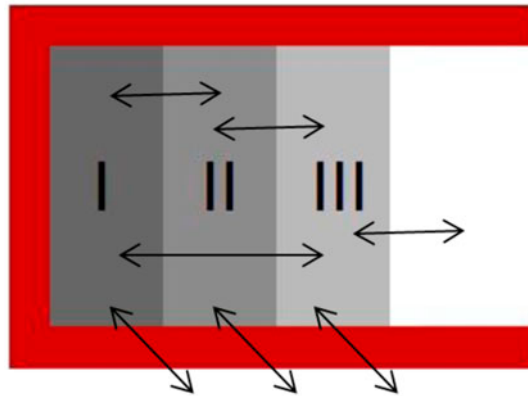


Figure 11. Classification of three regions within the bounding box (arrows represent the shapes moves).

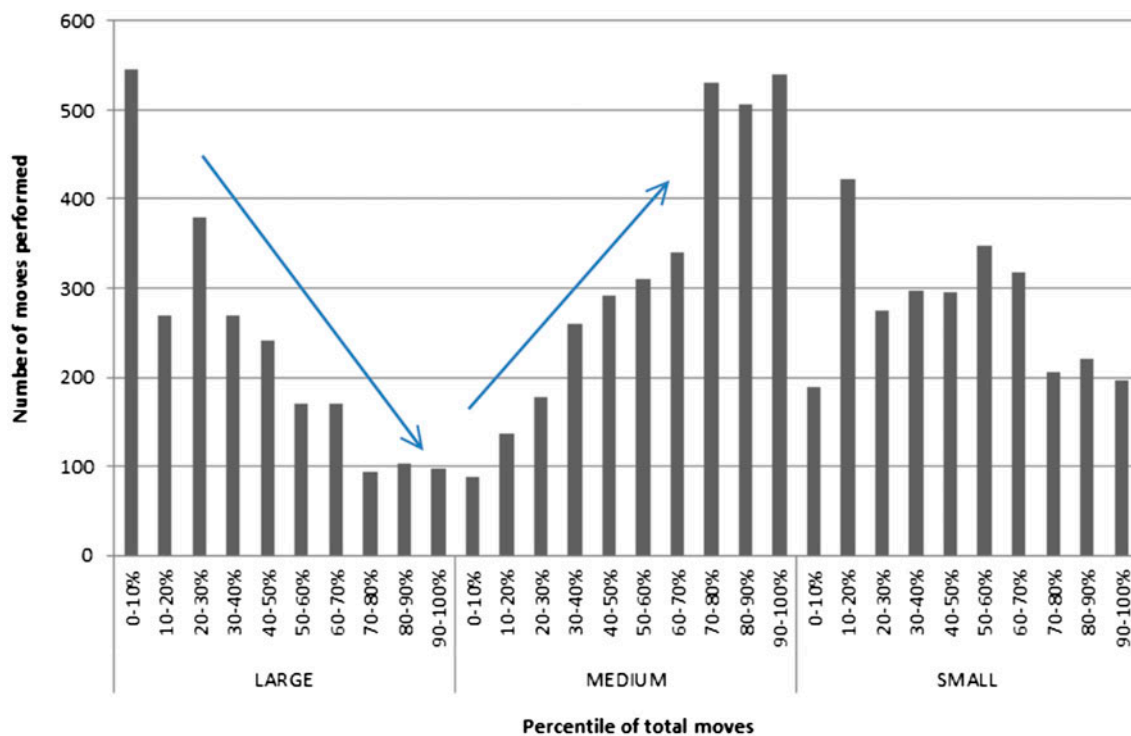


Figure 12. Cumulative number of moves performed by all workers on large, medium and small shapes throughout the Swim packing task.

These observations suggest that workers can visualise the efficient placement of larger shapes at the start of a layout process, while small shapes would appear to be used to fill vacant spaces as they are created in the process of carrying out the task.

6.2.2 Heuristic 2: left first placement preference

Figure 13 depicts the analysis carried out to investigate in which region of the packing area different sizes of shapes were mostly frequently manipulated. The outcome of this study further reinforced the notion that large shapes are handled first, as they appear mostly in region I, which is always the region where workers place the shapes first as they adopt a ‘left first’ placement strategy. Indeed, none of the workers started by packing the shapes into regions II or III. Medium-sized shapes tended to be located mainly in number III region of the packing area, which further consolidates

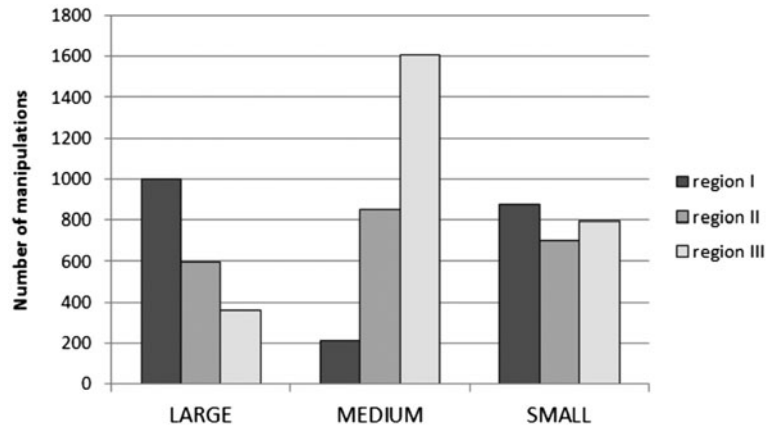


Figure 13. Cumulative number of manipulations performed by all workers on different sized shapes in different regions.

the previous finding (Figure 12) that suggests that the medium shapes are placed last. Again, there was no spatial preference displayed in case of small shapes. The regression analysis was studied to find influences of packing efficiency by shapes' manipulation in each region. A linear regression established that the number of shapes manipulated in region I and region II has positive influences on the packing efficiency. However, the number of shapes manipulated in region III has negative influences. The regression equation is: $\text{packing efficiency} = 65.883 + 0.007 \times (\text{number of manipulation in region I}) + 0.007 \times (\text{number of manipulation in region II}) - 0.005 \times (\text{number of manipulation in region III})$. This finding is verified in Figure 14 by comparing the manipulation performed by User-1 (lowest packing efficiency) and User-9 (highest packing efficiency). The number of shape manipulation preferences between the regions varies significantly between User-1 and User-9 which shows that higher movements in regions I and II could lead to high packing efficiency.

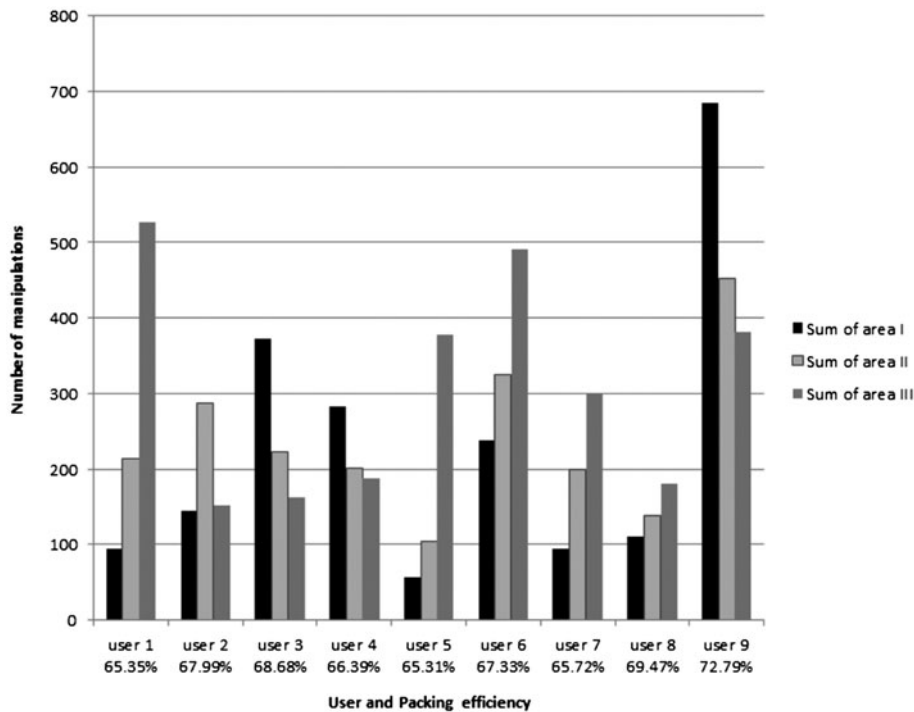


Figure 14. Cumulative number of manipulations performed by each worker in different regions and their packing efficiency.

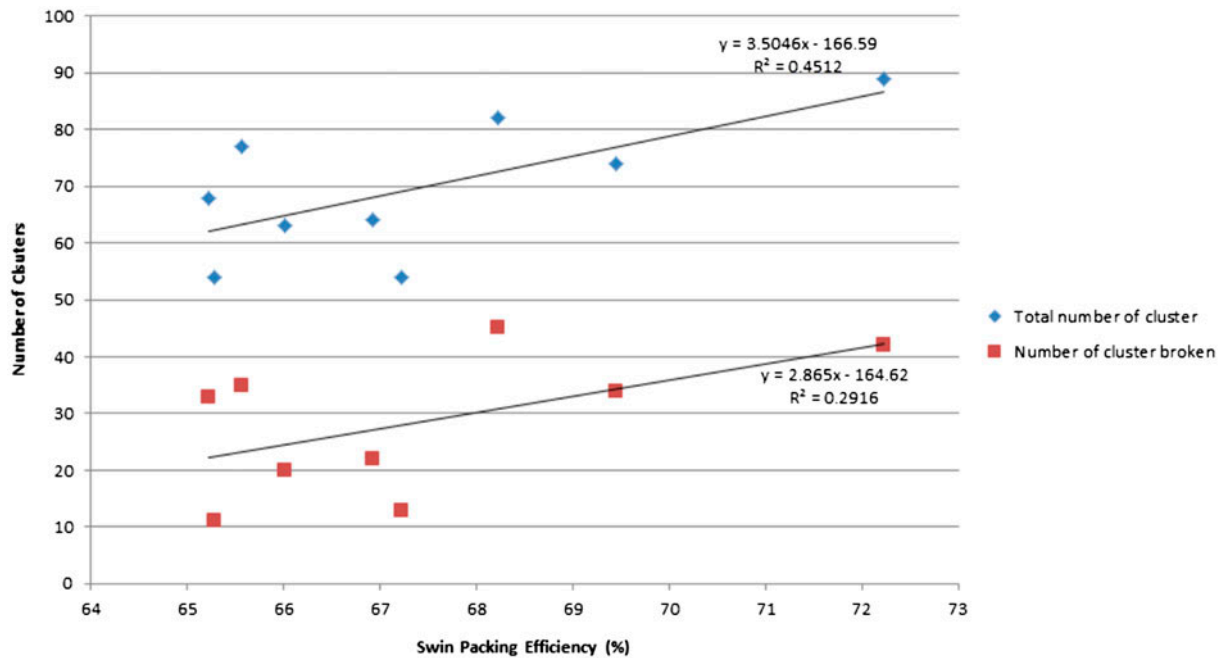


Figure 15. Total clusters generated and broken by each worker while doing on the Swim packing task.

6.2.3 Heuristic 3: maximise cluster size

Figure 15 shows the total number of clusters generated and destroyed by each worker while creating a nesting layout for the Swim data-set. The linear regression line demonstrates that higher the total number of clusters created during the arrangement process, the better the result. It also illustrates that the number of clusters generated by a human worker is comparatively modest (at only 89) compared to the combinatorial numbers an algorithmic approach (for arranging 48 shapes) might explore. This highlights the difference between algorithmic and manual approaches, where humans can frequently get excellent results from very restricted searches of potential huge solution spaces. Table 6 presents the coefficient of regression determination value for different number of clusters. It demonstrates that higher the number of clusters with two or six shapes, the better chances to get high packing efficiency.

6.2.4 Heuristic 4: breadth of search

Moving shapes between regions after shape placements and cluster breakages is also important because it broadens the space of layouts explored (i.e. variety of layouts examined) and would ultimately result in enhanced packing efficiency. The higher coefficient of regression determination (61.03%) between parameters in Figure 16 confirms this relationship (i.e. that high number of moves, either between regions or outside, leads to higher packing efficiency).

7. Discussion

The aim of this research was to investigate the feasibility of employing crowdsourcing (i.e. micro-outsourcing) to provide a service to solve industrial spatial optimisation tasks. Through systematic trials on an open crowdsourcing platform (mTurk), an effective user interface and task presentation for spatial optimisation tasks was identified. The best results were found to be obtained by allowing workers to see a picture of a nesting layout from a commercial CAM system. For two sets of 2SP tasks, this approach (i.e. illustration of known solution) provides better outcomes than either the text (i.e. the % value of best known score) or a blind approach (i.e. no information about known solutions). The reason for this could be the natural competitive trait of human workers which plays a key role in pushing humans to achieve higher limits. In this context, the target in picture format provides the needed impetus to achieve higher efficiency and explicitly shows what is possible.

Although the Scottish workers achieved consistently higher score than the Indians, this could be a result of different backgrounds rather than inherent ability. Inherent ability refers to the workers' ability to reason about shape, as distinct

Table 6. Coefficient of regression determination for number of cluster combination.

Number of cluster combination	Coefficient of determination (R^2 value)
Two	0.3384
Three	0.2735
Four	0.0042
Five	0.2698
Six	0.6545

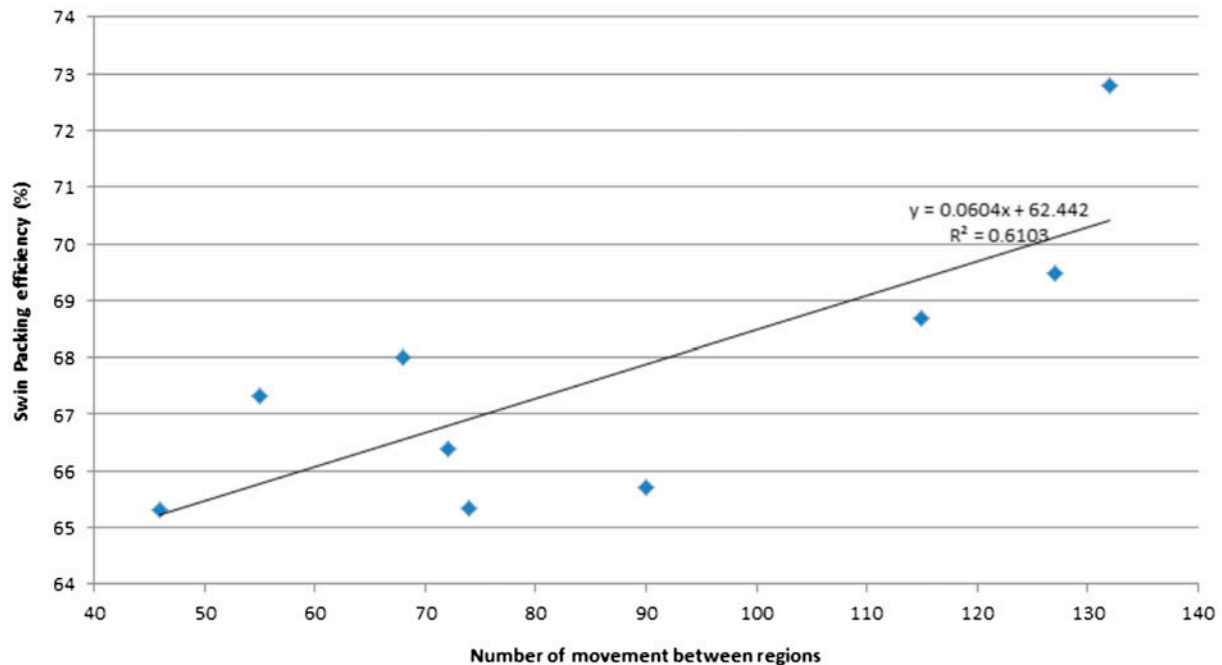


Figure 16. Number of movement between regions used by each worker.

from their experience with interactive computer graphics. The demographics of Indian and Scottish rural workers are, for example, very different in terms of age and work experience. Most Indian BPO workers are young, school passouts and new to paid employment (having less than 3 years of experience), whereas the Scottish homeworkers are aged, educated and experienced (having more than 5 years of experience).

Despite these differences, the packing results demonstrate that with even minimal training, both Scottish and Indian rural workers could achieve better efficiency than the commercial software baseline. Although the Scottish homeworkers achieved the highest packing efficiency (in less time) for most of the benchmark tasks, the rural Indian workers (despite being more familiar with text-based data entry work in their daily jobs) produced a performance in solving the 2SP problems comparable to Scotland's Internet homeworkers, who are more frequently exposed to interactive computer graphics (such as games).

So, although rural Indian workers lack exposure to interactive shape manipulation environments, they, with minimal practise, achieved high packing efficiency scores for 2SP problems. The results also provided insights into human strategies associated with achieving high packing scores. For example, the use of 'nudge movements' highlights that solving packing tasks require significant amounts of incremental adjustment movements between shapes. The high usage of flip movements by the Scottish homeworkers demonstrates their good spatial reasoning ability and its importance in their strategy for obtaining high packing scores. So, while the Scottish homeworkers are more consistent in their ability to produce high packing tasks efficiencies, their costs (\$10/h) are significantly higher than rural Indian BPO workers (\$2/h).

The investigation of more sophisticated pattern of behaviour associated with the heuristic packing strategies adopted by the human workers suggests that they: (1) locate more large shapes than small ones in the initial stages of the packing process; (2) adopt a 'left first' placement approach; and (3) obtain higher packing efficiency when they (i) explore (by trial and error) a larger number of shape clusters in the nested layout and (ii) make large movements of shapes

during the arrangement process. Although the analyses of packing strategy have been limited in their scope (only nine workers), the results demonstrate the potential of the data to generate insights into successfully nesting strategies that could potentially be useful in the creation of algorithmic approaches. As with any data analysis, the right questions have to be asked of the data and there are many other interesting questions that could be investigated. Further work is required to increase the sample size and statistical significance of the results.

These results demonstrate that rural workers, regardless of their educational or social background, are adept at manipulating and reasoning about shapes and produce better results than automated solutions generated by commercially available CAM software. The performance levels (i.e. packing efficiency and the time) reported here have established baselines against which manufacturers can use for cost and performance trade-offs between crowdsourcing and commercial CAM software to obtain the most efficient manufacturing operation. Essentially, the calculation is one that calculates if an average increase in packing efficiency of 4% gives sufficient reward in terms of materials saving to justify the costs of 1–2 h of crowdsourcing.

8. Conclusions

In this work, a novel CrowdPowered CAM approach to 2SP has been presented. Several experiments were conducted and the results suggest that crowdsourcing can be an effective approach to generate ‘good’ solutions to engineering problems, in particular packing problems for the price of a few dollars and a couple of hours. The results have also demonstrated that crowdsourcing provides a practical way to economically employ distributed human intelligence in the solution of combinatorial tasks like the strip packing problems. This is desirable because presently, reported computational algorithms can only just match the performance of human beings. For all data-sets, the best outcomes of commercial software were exceeded by the rural workers in India and Scotland. However, a crowdsourcing approach will also require ‘computational’ times that are much higher than the commercial CAM systems. Although this may not be a serious limitation, since a large number of people can be employed to work in ‘parallel’, allowing several layouts to be produced in a small amount of time. These results did not fully explore the effects of bonus payments and it could be possible to achieve efficiencies that exceed even the academic best results by repeating these experiments with the additional motivation of a cash reward for nesting layouts that improve upon the best research systems. The paper has also demonstrated that records of the individual worker’s actions can be used to investigate the existence of patterns in the behaviour of the most successful. Future work will explore the potential of extracting heuristics from the crowdsourcing solutions and feeding these back into the design of packing algorithms so as to increase their efficiency. This unique interaction between crowd and algorithms could take efficiency of these sorts of engineering tasks to another level, and also provide skilled work and income to rural workers who are currently lacking opportunities to benefit from the knowledge economy. Future work will also involve testing the developed CrowdPowered CAM platform with other interesting manufacturing problems, where automated solutions struggle to provide good solutions such as packing components in damaged leather sheets, and the multiple constraints found in the container loading problems of logistics platforms.

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