

Accepted Manuscript

DEM-based modelling framework for spray-dried powders in ceramic tiles industry. Part II: Solver implementation.

J.M. Tiscar^{a,*}, A. Escrig^a, G. Mallol^a, J. Boix^a, F.A. Gilabert^b

^a*Technological Institute for Ceramics (ITC), Jaume I University (UJI), Castellón; Spain*

^b*Department of Materials, Textiles and Chemical Engineering (MaTCh), Faculty of Engineering and Architecture (FEA), Ghent University (UGent), Technologiepark Zwijnaarde 46, B-9052, Zwijnaarde, Belgium*

Abstract

In the preceding Part I, a combined experimental-numerical study to characterize fine spray-dried powder used in the ceramic tile pressing process was presented. In the present Part II, the algorithm proposed by (Mazhar, 2011) to solve the numerical simulation of powder dynamics through the Discrete Element Method (DEM) was extended. In this paper, the original algorithm was adapted for efficient use on multi-core CPUs and a single GPU. In both cases, history-dependent contact models were considered. The efficiency of the algorithms was compared among them and with LIGGGHTS, a reference software package for particle simulation using DEM. The results demonstrated a higher performance of the codes developed compared to LIGGGHTS, particularly in demanding scenarios with a large number of particles (more than 1 million) of small size (median diameter in volume less than 1 mm). In particular, the CPU-based algorithm was suitable for simulating the mould filling in ceramic tiles industry.

Keywords: DEM, Parallel computing, GPU computing, multi-threading

*Corresponding author

Email address: juanmiguel.tiscar@itc.uji.es (J.M. Tiscar)

1. Introduction

Numerical simulation has become a useful tool to optimize and design industrial equipment. Concerning powder processing, the Discrete Element Method (DEM) [1] is widely used to simulate the granular behaviour, however it still involves excessive computational efforts [2–5]. In DEM, the Newton equations for translation and rotation are solved for each particle. This approach allows the use of contact models which reproduce the physical behaviour of the particles, helps to investigate granular flow characteristics and analyses the particle tracking. Different models of contact are present in literature, such as linear [6] and Hertz [7, 8] model. DEM is applied to an extensive range of physical and engineering problems, ranging from the study of agglomerates [9] (micro-scale) to rockfall dynamics [10] (macro-scale). In the context of the simulation of industrial processes, a huge number of particles must be modelled to obtain representative results, and despite the development of techniques for reducing the number of particles [11], simulating an industrial scenario used to involve an important computational effort.

One of the most used software packages in DEM simulations is LIGGGHTS [12], which is an open source software and an improved version of LAMMPS. LAMMPS is another open source software used in the field of molecular dynamics (MD) [13], based on a contact detection algorithm that relies on a uniform grid data structure handled by means of the well-known and widely-used linked-list data structure [14]. Regarding parallel computing, LIGGGHTS uses message-passing interface (MPI) to scale across multiple processing cores and take advantage of linked lists. Although it is a good method to obtain parallel code, some researches have proposed other algorithms in the multi-threaded computing approach [15, 16].

In addition to the CPU computing, nowadays, GPU computing is also used for

26 numerical simulations in different scientific fields [17–19]. Several reports have shown
27 a good performance of GPUs versus single CPU computing [20, 21], whilst other
28 researchers have noticed a similar performance for both multi-thread CPU and GPU
29 computing [22].

30 The main differences between both computing platforms are briefly described
31 below (refer to [23] for further description):

- 32 • Number of cores. Whilst the current CPUs consist of 4 or more cores, the
33 GPUs can have hundreds of independent cores. However, the clock frequency
34 of GPU cores is significantly lower than the CPU ones.
- 35 • Cache management. The single instruction multiple data (SIMD) model of
36 a GPU sets several cores to run the same code in parallel, so GPUs do not
37 provide a general cache for all memory accesses like CPUs. This design hides
38 the latency of memory accesses, but increases the overhead in the inter-core
39 communication through main memory.
- 40 • Algorithm design. The development of scientific applications on GPUs used
41 to be more challenging and more complex than on CPUs [17]. The partic-
42 ular architecture of the GPUs implies using all cores and avoiding inter-core
43 communications (limiting concurrency capabilities) to get a high performance.

44 There are also algorithms based on a CPU-GPU hybrid computation that demon-
45 strate an opportunity to improve, for example, the simulations of gas-solid two-phase
46 flows [24, 25]. In this context, Mazhar et al. [26] developed a remarkable parallel
47 collision detection algorithm for multibody problems suitable to be carried out in
48 two levels using CPU-GPU hybrid computing. This algorithm overcomes some lim-
49 itations regarding the use of linked list, such as the process of selecting the optimal

50 cell size. However, it is focused on a hybrid computing platform regardless of the
51 physical model underlying the detection. In this work, Mazhar's detection algorithm
52 is extended and specially modified to be independently executed in a multi-core CPU
53 or in a single GPU.

54 Multi-thread computing is usually faster than the sequential one, specially in
55 DEM simulations, but the decision whether to use a CPU or GPU code for multi-
56 thread computing is not straightforward. The small- and medium-sized industrial
57 powder-related sectors are sometimes reluctant to use large calculation clusters for
58 simulation and modelling activities. At least in the ceramic tile manufacturing sector,
59 the affordability and simplicity of the technology are a crucial factor in the modelling
60 process. Hence the interest in being able to perform DEM simulations on non-
61 specialized or low-cost equipment.

62 After conducting a literature review, it has been found that many studies simplify
63 the computations to demonstrate the speed-up of the GPU computing versus CPU,
64 although these simplifications could call into question the accuracy and reliability of
65 the model. For example, Govender et al. [27] showed an important speed-up in DEM
66 simulations via GPU computing, but using a history-independent contact model with
67 a special mesh treatment [28]. On the other hand, Radeke et al. [21] claimed that
68 their GPU code is able to simulate the behaviour of one million particles during
69 one physical minute in about four days of wall-clock time. However, their code
70 works on single-precision floating-point format, and a special treatment is needed
71 to achieve a good accuracy [29]. Note that the GPU double-precision capability is
72 significantly slower than the single-precision one [30]. Also the GPU code of Zheng
73 et al. [31] exhibited an increment in efficiency of about 73 speed-up ratio compared
74 with the CPU algorithm. However, they use a threshold value to limit the maximum
75 number of particles in a cell and another threshold value to limit the maximum

76 number of contacts of a particle. These considerations allow the use of the shared
77 memory in GPU computing, which increases the performance, and facilitates reading
78 and writing of contact history. As a consequence, the code is limited to simple
79 geometries and narrow particle size distributions. Recently, Gan et al. [32] used
80 a new algorithm [33, 34] to evaluate its performance on a single-GPU, multi-GPU
81 and CPU configurations. They demonstrated that a single GPU outperforms CPU
82 when simulating mono-sized particles. This also occurs for a multi-GPU computing
83 with elliptical particles, which was industrially validated [35]. However, even though
84 history-dependent models can be used, it requires to limit the maximum number of
85 contacts of each particle. In fact, the use of threshold values that limit the number
86 of contacts of each particle is still used in the latest reference dealing with GPU
87 algorithms [36].

88 In response, opposing studies have also arisen that exemplify the scepticism that
89 exists regarding the vast superiority of GPUs over CPUs in the massive paralleliza-
90 tion of scientific computing algorithms. Lee et al. [23] showed how, with regard to
91 scientific calculation, the enormous differences announced between the two process-
92 ing units are of dubious credibility, while other studies showed that over-simplistic
93 programming can lead to disappointing results [37]. Regarding DEM, Shigeto et
94 al. [22] emphasized that the comparison between the use of both calculation archi-
95 tectures must be realistic and fair, evidencing that the enormous differences between
96 them revealed by some researchers are far from fulfilling both principles. In addition,
97 Washizawa et al. [38] stated that the computational speed of a practical DEM model
98 is significantly slower to run on a GPU than on a CPU.

99 As it has been seen, there is a lack of clarity comparing CPU and GPU algorithms
100 in equal conditions. In this work, an extension and modification of the Mazhar's de-
101 tection algorithm is introduced in an in-house developed DEM solver. This proposal

102 enables the use of complex physical models and do not require expensive nor tech-
103 nically complex HPC facilities to simulate large particle assemblies, but it can still
104 exploit the multi-core features of conventional desktop or laptop computers. Further-
105 more, no limiting parameters are required that have to be defined manually at the
106 beginning of the computation. Additionally, the key ideas of this proposal have been
107 extended and integrated in two different versions of the solver, suitable for running
108 on a multi-core CPU and a single dedicated GPU, respectively. Both solvers have
109 been benchmarked against LIGGGHTS.

110 The present modified solvers still keeps the advantages of the Mazhar's algorithm
111 but it also covers very important aspects:

- 112 (i) An efficient layout to cope with the particularities of the physics of the contact
113 model (storage and access to the contact history, regardless of the number of
114 contacts).
- 115 (ii) A general treatment for the boundaries, whose handling is similar to that of
116 powder particles. Definition of the calculation domain is never needed.
- 117 (iii) An efficient layout allowing for running large-scale simulations in low perfor-
118 mance equipments with non-abundant RAM memory.
- 119 (iv) A simple layout that avoids the use of manually predefined parameters, which
120 facilitates the usage of the solver without compromising the reliability of the
121 results.

122 This paper is organized as follows: the process flow for DEM simulations is
123 summarized in Section 2; the extension of Mazhar's algorithm for multi-core CPU and
124 single GPU platforms are explained in Section 3; Section 4 compares the performance
125 of the two algorithms showed in Section 3 with LIGGGHTS, and discusses their
126 applicability; finally, a few conclusions with several final remarks are presented. The

127 [equipment and programming specifications used in this work are included in the](#)
128 [Appendix A.](#)

129 **2. The scheme of the DEM simulations**

130 The general DEM scheme consists in updating the kinematics and dynamics of a
131 system constituted by the so-called "discrete elements". These elements are physical
132 objects that can interact with each other and can represent either individual particles
133 or any other basic geometric entity capable of interaction. The physics governing the
134 contact between the discrete elements depends on the selected constitutive models.
135 As presented in Part I, these models are described by a set of mathematical equations
136 representing the material response under different loads. Although simplifications
137 are always assumed, the main physical features must be retained in order to agree
138 with the experimental observations. The equations of motion incorporating these
139 physically-based contact models are numerically integrated, where the contact forces
140 and transferred moments between elements are continuously computed over time.
141 Therefore, DEM is a very suitable simulation method to accurately describe the
142 complex motion of big assemblies of elements like rocks, stones, powders, granules,
143 seeds, etc. Conversely, DEM is not suitable to study the stress and strain fields
144 inside the elements, unless coupling with other continuous-based numerical method
145 is considered, like the finite element method (FEM).

146 In the present work, the granules of the spray-dried powder are physical objects
147 modelled as spheres. The boundaries of the setup confining the powder (e.g., rotating
148 drum, mixer, mould feeder, conveying belt, etc.) are meshed using triangles.

149 Fig. 2 shows a general DEM flowchart. First, all variables are initialized, as
150 the domain parameters, the contact model, the integrator scheme and the mesh
151 movements, amongst others. Second, the geometry and particles are indexed in the

152 simulation scope and the data structure is created. Once all parameters are prepared,
153 if the simulation involves GPU computing, the requested information is copied to the
154 GPU.

155 Subsequently, contacts between objects are detected, the forces are calculated
156 and finally an integrator scheme is applied in order to update the particle positions.
157 Afterwards, if these stages are executed on the GPU, the relevant information is
158 copied back to the CPU. These operations are repeated iteratively until the final
159 time is achieved. Furthermore, if the confining boundaries experience any type of
160 motion, all their geometrical elements must be updated at the beginning of the next
161 time increment. Generally speaking, the three basic stages in a DEM solver are:

- 162 (i) The collision detection algorithm that foresees and registers all the contacts
163 between the elements.
- 164 (ii) The calculation of forces.
- 165 (iii) The numerical integration scheme that updates all positions.

166 Likewise, the collision detection process is typically the most demanding computa-
167 tional stage, followed by the force calculation and finally by the integration scheme
168 [39]. The simplest searching algorithms to detect pair of elements under interaction
169 usually lead to a computational complexity of $\mathcal{O}(n^2)$, meaning that the amount of
170 time and memory scales as the number of elements is squared [40].

171 However, the most efficient and sequential collision detection algorithms can lead
172 to a computational complexity of $\mathcal{O}(n)$. These algorithms are based on performing
173 the so called “[space subdivision](#)” process, consisting in dividing the physical space in
174 small “cells” or “bins”. This process greatly reduces the amount of evaluations be-
175 cause only the element pairs inside neighbouring cells are checked. This [subdivision](#)
176 can be performed by using uniform bins, quadtrees, octrees or by any other topo-

177 logical arrangement. The evenly distributed bin approach is commonly used due to
178 its good ratio performance to implementation cost. Having said that, the main dif-
179 ferences between algorithms rely on the structure and management of the data [41].
180 Moreover, this subdivision is fully independent of the computational platform.

181 With the aim of reducing the computational cost even more, all these algorithms
182 can be implemented taking advantage of the parallelism of modern multi-core plat-
183 forms. Here it is important to remark that computational complexity $\mathcal{O}(n)$ is unal-
184 tered, as n is an invariant.

185 This work proposes a set of algorithms focused on reducing the computational
186 cost by means of parallelizing the collision detection and force computation stages.
187 The algorithms are an extension of Mazhar's algorithm for multi-core CPU and single
188 GPU platforms. The description of how the initialization and the integration stages
189 are parallelized, as well as the boundary movements, is omitted in this paper due to
190 their minor impact on the final performance of the algorithms. Finally, note that
191 this paper presents two independent algorithms for CPU and GPU computing, but
192 not for a hybrid computing like the original proposal [26].

193 3. Algorithms for DEM computing

194 Traditionally, contact detection for DEM simulations has been performed using
195 a two-phase approach based on a linked-list structure [14]. A linked list is a linear
196 data structure where the elements are not stored at contiguous memory locations.
197 It is a dynamic data structure which enables a fast insertion and deletion data, and
198 efficient memory utilization. This structure is used by most DEM software, such
199 as LIGGGHTS [12]. Despite its efficiency, this strategy has two major drawbacks.
200 Firstly, all cells of the domain have to be evaluated even though they do not contain

201 objects. If the domain is big, it can lead to important memory limitations. Sec-
202 ondly, for the contact evaluation, searching is limited to all objects in the given cell
203 and in the neighbouring cells (2 cells in 1D, 8 cells in 2D and 26 in 3D). Therefore,
204 the minimum size of a cell has to be the same as the largest element in the system
205 to ensure a correct evaluation. It involves an important limitation if the elements
206 are very different in size, because it worsens load balance on multi-core platform.
207 Poor load balancing can be avoided by increasing the cell size, however, decreasing
208 the number of cells might imply an increase in the order of complexity of the algo-
209 rithm. Consequently, a pre-analysis step is usually required to run efficient DEM
210 computations [42].

211 In order to avoid these disadvantages, in this work a strategy inspired by that
212 used by Mazhar et al. [26] has been developed. This new proposal extends the
213 Mazhar's strategy, describing how to track the previous contact history, required in
214 some constitutive models, and reducing dramatically the memory usage. The latter
215 is specially relevant to simulate big assemblies of discrete elements (>1 million of
216 elements).

217 *3.1. Boundary treatment*

218 As stated above, in this work the boundaries are meshed using triangles. This
219 triangles are, in turn, decomposed into simpler elements, also considered as discrete
220 elements (or boundary elements). Consequently, the boundary becomes part of the
221 data structure of the model, consisting of granule, face, edge and vertex type ele-
222 ments. Figure 3(a) exemplifies a mesh. Note that while all faces must be part of the
223 data structure of the model, not all the edge and vertex elements need to take part
224 on it. Only the outer edges and vertices are likely to be in single contact with the
225 granules (figure 4). On the one hand, the outer edges are considered to be those that

226 belong to several faces, as long as one of them is not coplanar with the others, or
227 those that belong only to one face. On the other hand, outer vertices are only those
228 that belong to non-collinear edges.

229 Since a granule can be in contact with several geometric elements at the same
230 time, it is necessary to establish rules to avoid multiple contacts arising from the
231 same boundary. Therefore, when detecting a contact with a boundary element, it is
232 necessary to validate the contact to ensure its uniqueness. The checking rules are
233 defined as follows:

- 234 1. A granule is in contact with a face element. It is validated without any addi-
235 tional condition.
- 236 2. A granule is in contact with an edge. It is validated only if the granule is not
237 in contact with a face containing that edge.
- 238 3. A granule is in contact with a vertex. It is validated only if the granule is not
239 in contact with any edge or face connected to that vertex.

240 The proposed methodology is inspired by the procedure established by Su et al. [43] to
241 perform simulations of particles flow in arbitrary complex geometries. Figure 4 shows
242 the three possible scenarios of a granule in contact with the boundary. In scenario 1,
243 the centroid of the granule can be projected into the face and the granule-face contact
244 is detected. In scenario 2, the centroid of the granule cannot be projected into the
245 face, so the granule-face contact is not identified. Thus, a granule-edge contact is
246 detected. In scenario 3, the centroid of the granule cannot be projected neither into
247 the face nor into the edge, so that only the granule-vertex contact can be detected.
248 The checking rules stated above must be applied for each detection.

249 *3.2. DEM Algorithm on a CPU*

250 The following algorithm is based on Mazhar's algorithm [26], whose memory
 251 management is excellent. It is focused on the sorting, which is extremely fast in GPU
 252 computing, specially using the radix sort. A similar strategy can be addressed to the
 253 multi-core CPU computing introducing some variations in the original proposal.

254 On the other hand, the original strategy only considers sphere-sphere interactions
 255 because the domain is spherically decomposed. How to track the contact history is
 256 not discussed. In the following, a general algorithm for DEM simulations focused
 257 on multi-core CPU computing is explained together with the tracking of the contact
 258 history. The latter feature enables the use of realistic contact models, such as those
 259 which consider the tangential micro-slip [44] during the contact.

260 *Stage 1. Indexation.* This stage begins by identifying all the intersections pro-
 261 duced between the elements and the cells surrounding them. Figure 3(b) shows a
 262 geometry and the cells surrounding that geometry, where only the cells intersect-
 263 ing those elements are indexed. The size of the cells is defined as twice the mean
 264 diameter of all the granular elements.

265 For each element, the maximum and minimum points that delimit its position
 266 in the domain are determined by means of a bounding box and the cells owning
 267 those points are identified. Figure 5 shows an example of the bounding box and the
 268 bounding points of a granular and edge element.

269 The number of cells (N_{cells}) intercepting any granular element is given by:

$$N_{cells} = (I_{max} - I_{min} + 1)(J_{max} - J_{min} + 1)(K_{max} - K_{min} + 1) \quad (1)$$

270 where $\{I_{min}, J_{min}, K_{min}\}$ and $\{I_{max}, J_{max}, K_{max}\}$ are the cell coordinates of the
 271 bounding points of that element (this ternary is hereinafter denoted by *Coord*). In
 272 the 2D case presented in figure 5, the granular element occupies 4 cells and the edge

273 element occupies 3 cells. Following this construction, it can be noted that a vertex
274 element only occupies 1 cell. It is important to remark that faces (or edges) are, in
275 general, arbitrarily oriented, thus generating a bounding box that may span a big
276 number of cells, as equation 1 states. Obviously, this situation is highly inefficient
277 because most of the cells in the bounding box may be empty. To overcome this
278 drawback, this work adopts the algorithms proposed by the references [45] and [46]
279 to efficiently index the cells surrounding edges and faces, respectively. The algorithm
280 to index the cells surrounding edges registers only the cells visited by a 3D line
281 with endpoints on the grid. The algorithm to surround the faces by cells scans the
282 original bounding that encloses the face and then applies a filter equation. This
283 filter evaluates the distance between the cell and the face, wherein only the cells
284 intersecting the face are labelled and stored.

285 In order to parallelise this indexation stage, the supporting arrays A1 and A2 are
286 defined. A1 has a size equal to the number of elements, and its function is to store
287 the number of cells occupied by each element, as figure 6 shows. Array A2 is used to
288 save the cumulative sum of A1, wherein each entry contains the memory shift of the
289 corresponding location in A1. Counting the number of cells occupied by each element
290 and the creation of A2 can be done in parallel without risk of race conditions¹, since
291 the number of elements in the simulation is known at the beginning of this stage.

292 *Stage 2. Grouping the neighbouring contacts.* The next step is to put in con-
293 tiguous cells all those elements that may potentially be in contact. This is done in
294 the same way as in Stage 1, but instead of counting the number of cells, the cell

¹A race condition is an undesirable situation that occurs when two or more execution threads perform operations at the same time over shared resource, and the results may change depending on the order of execution.

295 information is stored. For this purpose, a new array A3 is created. A3 includes the
296 *Coord* variables that contains a given element as well as the element ID (*ID_Elem*).
297 Figure 7 shows this operation, where it can be seen that thanks to the memory shifts
298 saved by A2, this process can be fully parallelised.

299 Finally, A3 is sorted according to *Coord*, so that all elements occupying the same
300 cell are arranged contiguously. It is worth mentioning that two elements occupying
301 the same cell is a necessary condition but not sufficient to set up contact.

302 *Stage 3. Contact identification.* The main differences between the proposed
303 algorithm and the one proposed by Mazhar start at this stage. After sorting, A3 is
304 divided into as many chunks as threads can be simultaneously launched in the CPU.
305 Then, each thread identifies the real contacts in the cells of its chunk.

306 Figure 8 exemplifies the contact identification with 3 parallel threads: all posi-
307 tions of A3 corresponding to the same cell are coloured in the same colour, and the
308 *ID_Elem* is the number that appears in each position of the array. The different
309 line styles correspond to the contact evaluations made by processing threads 1, 2 and
310 3, respectively. On the other hand, the colour of the arrows indicates the number
311 of iterations performed by a thread for each position in A3. For example, focusing
312 on the first chunk (thread 1), a forward evaluation with 4 iterations is performed as
313 follows:

- 314 1. Checking contacts between elements 1-4, 1-10 and 1-41.
- 315 2. Checking contacts between elements 4-10 and 4-41.
- 316 3. Checking contact 10-41.
- 317 4. Checking contact 3-5, 3-7, 3-32 and 3-33.

318 It can be noted that this methodology might lead to the identification of a particular
319 contact in different cells. Nevertheless, the contact uniqueness in the cells can be

320 ensured by means of the collision centre, a concept suggested by Mazhar for the
321 granule-granule contact. This idea is here extended to deal with the granule-vertex,
322 granule-edge and granule-face contacts. In such cases, the centre of collision coincides
323 with the projection of the centre of the granule on the corresponding element.

324 *Stage 4. Forces and moments calculation.* This stage can be performed efficiently
325 and without race conditions by incorporating a critical section² in the code after the
326 contact checking.

327 Algorithm 1 exemplifies this procedure for two granular elements, although it is
328 also applicable to evaluate the contact between other element types. In Lines 3-5
329 the forces and moments are computed. These magnitudes are subsequently added to
330 each element in Lines 14, 15, 18 and 19. The procedure is free from race conditions
331 by means of a locking mechanism, as showed in Lines 13, 16, 17 and 20. Once the
332 elements in contact are known, the application of the physical model is direct as
333 long as the previous contact history is not required. However, most of the physical
334 models need to retrieve the previous contact history to calculate the current forces
335 and moments [47].

336 Algorithm 2 describes how the previous contact history can be extracted if it ex-
337 ists. Once the contact is identified, the contact history is retrieved from a contact list
338 that each granule is associated with. First, in Lines 7-12 the lowest indexed granular
339 element that constitutes the contact is checked to see if it contains information from
340 a previous contact with the second element. If so, this information is returned in
341 Line 10. Otherwise, a new contact is created in Line 14 and appended in Line 15 to
342 the contact list of the lowest indexed granule element. The used contacts are marked

²A critical section is a shared resource of a computer that can only be accessed by one execution thread at a time.

343 as active in Lines 9 and 14 to track the previous history used in each iteration. Once
344 the forces and moments are computed, the contact history is rewritten with the new
345 information generated so that it can be retrieved in the next iteration. The process
346 can be boosted by using a stable sorting algorithm in A3, which maintains the origi-
347 nal relative order of the elements. This ensures that the elements are sorted not only
348 according to the cell coordinates but also by their identifiers (figure 8). Finally, all
349 contacts that are not marked as active are removed from the contact lists.

350 *3.3. DEM Algorithm on a GPU*

351 The code developed to run on a single GPU is inevitably more complex than that
352 for the CPU due to restrictions in programming language, memory and communica-
353 tion management. On the one hand, the maximum amount of RAM available on a
354 GPU is typically less than that available on a CPU. Therefore, developing an effec-
355 tive GPU-oriented code enforces an efficient and wise memory usage. On the other
356 hand, while the GPU has a large number of cores (allowing massive parallelization of
357 code), the performance of these cores is limited to run relatively simple code with a
358 balanced workload to avoid the so-called “branch divergence” [48–50]. This happens
359 when threads executed in a same block (or warp³) run through different instructions
360 controlled by conditional statements. This situation must be avoided as non-equally
361 conditioned branch split can unbalance the workflow.

362 The following describes the algorithm used for DEM computing on GPU archi-
363 tecture, paying attention to the differences with respect to the CPU-based scheme.

364 *Stage 1. Indexation.* After transferring all the necessary information (geometry,
365 global values, tags, etc.) from the system to the GPU memory, this step performs

³A warp is a set of 32 threads within a thread block such that all the threads in a warp execute the same instruction.

366 the same actions as *Stage 1* in the CPU-based architecture.

367 *Stage 2. Grouping of neighbouring contacts.* This stage is performed in the same
368 way as *Stage 2* for the CPU architecture.

369 *Stage 3. Contact identification.* This stage starts after grouping array A3 (ob-
370 tained in *Stage 2*) using a stable sorting algorithm to reduce the branch divergence
371 in the next steps. In order to improve the understanding of the following parts of the
372 algorithm, Figure 9 contains a flowchart of the complementary arrays created from
373 A3 and their usage. Arrays A4, A5 and A6 facilitate the efficient GPU storage and
374 kernel executions. Arrays A7 and A7p store the contacts, while A8, A9 and A10 make
375 it possible to store the force and moments of each contact without the use of atomic
376 operations. Note that atomic operations, depending on its implementation mode,
377 might lead to significant bottlenecks in the performance of a GPU algorithm [51].

378 To analyse A3 in parallel, as many execution threads as cells are executed. This
379 strategy, different from the one performed in the section 3.2, reduces the branch
380 divergence and helps to balance the workload on the GPU cores. It requires creating
381 an array A4, which contains the cells offsets of A3.

382 Figure 10 sketches the layout of A4 and algorithm 3 shows its construction via
383 pseudocode. The construction of A4 proceeds as follows. In Line 3, A4 is defined
384 and allocated using the same size as A3 with all values initialized to *0xffff*. This
385 hexadecimal number is the largest unsigned integer value of 32 bits possible on x86
386 architectures. In Lines 9 and 10, every position of A3 is analysed by separated
387 threads where two conditions are checked:

- 388 (i) Whether that element is the first one in its cell.
- 389 (ii) Whether that cell contains more elements.

390 If (i) and (ii) are fulfilled, the index of its position is assigned to the same location in

391 A4 as line 11 shows. Finally, in Line 14 array A4 is sorted. This allows for keeping
392 on the left side all values other than *0xffff* and whose value is the position of the first
393 element of each cell in array A3 that may contain contacts. The finalized array A4
394 can be seen in figure 10.

395 The next step is to identify the contacts in parallel. First, the number of contacts
396 in each cell is identified and counted to perform the memory allocation of the contacts
397 history. Secondly, the number of contacts in each cell is identified again, and their
398 history is stored in the previously allocated memory space. It is noticeable that in
399 the CPU algorithm the contacts are only identified once, since a dynamic memory
400 allocation can be done on-the-fly.

401 The counting procedure is outlined in figure 11 and described via pseudocode in
402 algorithm 4 as follows. In Line 4 an intermediate array (A5) is defined and allocated
403 with a size equal to the number of cells with different values of *0xffff* in A4 (hereinafter
404 called active cells). In Line 6, as many processing threads as number of active cells
405 in A4 are executed. Each thread counts the number of contacts of its assigned cell
406 by brute force, as described in Lines 9-20. Finally, in Line 21 the total number of
407 contacts of the cell is stored in A5.

408 Similar to the construction process of A2 from A1 (see figure 6), the array A6 is
409 created to store the accumulated sum of A5. Once the number of contacts is known,
410 a new array A7 is allocated, where the contact history can be written without race
411 conditions. A7 is filled by re-identifying the contacts and using A5 and A6, similarly
412 as performed with A3 (see figure 7).

413 Previous contact history can be efficiently obtained by an extra step after writing
414 the array A7. To do that, two arrays are kept in memory: A7 for the current instant
415 (t) and A7p for the previous instant (t- Δt). The only requirement is to know the
416 position of every contact at both instants, as long as both exist.

417 Figure 12 and algorithm 5 show the process of linking A7 to A7p with a sketch
418 and pseudocode, respectively. In Line 5, a parallel thread is executed for each com-
419 ponent of array A7. In Line 7, every thread has to identify whether the current
420 contact existed at $t-\Delta t$. If so, the cell coordinates containing this contact history
421 (*Old_Coord*) are retrieved, otherwise, a null value is returned. This checking is
422 needed because it might happen that the cell that evaluates the contact changes
423 with the movement of the elements. Line 8 checks if the current contact is new, in
424 which case its history is initialized in Line 9.

425 If the current contact exists in A7p, *Old_Coord* is now known and the cell where
426 the contact occurred is searched in A7p using a binary search, as shown in Line
427 12. The binary search, of $\mathcal{O}(\log n)$, is possible because A7 is naturally ordered by
428 cell coordinates. After finding the cell, the contact is found using a linear search.
429 In Lines 13-22 a backward linear search is described. Line 15 checks whether the
430 elements in contact are those desired. If so, Line 16 updates the history in A7. If
431 not, Line 19 reduces the array index. If after completing the backward linear search
432 the contact history has not been found, Lines 22-30 perform a forward linear search
433 in the same way.

434 Finally, note that the branch divergence can be reduced by evaluating the contacts
435 in a staggered manner (first the granule-granule contacts, second the granule-face
436 contacts...).

437 *Stage 3. Forces and momentums assignment.* This part also requires extra stages
438 compared to the CPU code, due to the peculiarities of the GPU, which imply max-
439 imizing code parallelization while minimizing code concurrency. Figure 13 sketches
440 this assignment and algorithm 6 describes the procedure via pseudocode. Arrays A8,
441 A9 and A10 are created and allocated with a size equal to twice the size of A7 and
442 initialized to *0xffff* as shown in Lines 4-7. In Line 8, as many processing threads as

443 number of contacts are executed. In Line 9, the forces and moments of each contact
444 are computed by the corresponding thread. For the first element in contact, its iden-
445 tifier, force and moment are set in the corresponding positions of A8, A9 and A10 as
446 observed in Lines 10-12. For the second element in contact, Line 13 checks whether
447 it is a granule element. If so, its identifier, force and moment are set in Lines 14-16.

448 In Line 19, A9 and A10 are sorted by key, using as key A8. Then, A9 and A10 are
449 reduced in Line 20, and the position of the first geometrical element in A8 is checked
450 in Line 21. After these operations, A9 and A10 contain the total forces and moments
451 for each granule element. Finally, in Lines 22-25 the new forces and moments are
452 transferred to the granule elements without race conditions and in parallel.

453 **4. Performance Analysis**

454 The algorithms previously described were implemented on both multi-core CPU
455 and single GPU platforms, and were analysed together with the software LIGGGHTS.
456 [The equipment and programming specifications used for the analysis are described](#)
457 [in Appendix A](#). The three DEM codes were compared among them to analyse the
458 effect of number of granules and its polydispersity in their performance. The capabil-
459 ities of each code were evaluated simulating a mould filling, which is a crucial stage
460 in the ceramic tile forming process. Basically, it involves pouring in a mould, via a
461 transportation system, a certain amount of powder (usually a spray-dried powder).

462 The study consisted in filling a small mould (figure 14). The system was composed
463 of three objects: a hopper, a feeder and a mould. In total, eight different Grain Size
464 Distributions (GSD) were tested with a median granule size in volume (d_{50}) of 3 and
465 0.5 mm and a geometric standard deviation (σ_{geo}) of 1, 1.2, 1.4 and 2, respectively. In
466 the ceramic tile industry, tiles manufactured in a mould of this size are considered to
467 be small-sized tiles, so the results obtained here can be relatively extrapolated to the

468 industrial mould filling. Table 1 summarises all simulations performed in this section.
469 Each simulation was labelled depending on its group, polydispersity and the code
470 used. The simulations were split in two groups: group A includes the simulations
471 with a d_{50} of 3 mm, and group B those with a d_{50} of 0.5 mm. Three DEM codes
472 were tested: the code developed to be used in a CPU platform, the one to be used
473 in a GPU platform and the code of LIGGGHTS executed in a CPU platform. In
474 each group, and for each code, four simulations were executed with different levels of
475 polydispersity. Table 1 also includes the number of granules and the timestep used
476 in each simulation.

477 *4.1. Simulation conditions*

478 Figure 15 depicts the three different phases of the mould filling simulations, taking
479 simulation A4 as example. Initially the powder is poured into the feeder while the
480 hopper is moving backwards (figure 15(a)). Following, the feeder moves forward
481 depositing the powder into the mould (figure 15(b)). Finally, the feeder returns to
482 its original position (figure 15(c)).

483 The number of granules varied between $8.7 \cdot 10^4$ and $1.3 \cdot 10^6$, depending on
484 the simulation. The physical model used was the Linear Spring-Dashpot (LSD)
485 model [52]. Imposing properties that require very low time steps in integration does
486 not make sense given the comparative nature of the analysis. However, similar values
487 for granule density and stiffness to those calibrated in [52] were used. All properties
488 and parameters were kept constant, independently of the code used. However, de-
489 pending on the granular distribution used, the time step was revised. On the other
490 hand, LIGGGHTS incorporates the LSD model in a different way from the codes
491 developed [12], so in order to impose a similar behaviour in all codes, it was de-
492 cided to eliminate the rolling resistance and the viscous damping. [Table 2 shows the](#)

493 properties of the granular material used in all cases in this study. In addition, the
494 default cell size of LIGGGHTS was used, which coincides with the maximum size of
495 the largest granule.

496 Powder distribution was generated previously in order to fill the hopper by grav-
497 ity. As a consequence, all initial conditions in the mould filling simulations contained
498 the particles deposited on the hooper, which reduced the physical time of the simu-
499 lations.

500 *4.2. Results*

501 Performance results conducted are described below. The performance was evalu-
502 ated by measuring the total time of each simulation using the time command provided
503 by Linux. The results are detailed in two separate groups as given in table 1, and
504 discussed later.

505 *4.2.1. Group A*

506 Figure 16 compares the average elapsed time per iteration as function of the
507 number of contacts in different simulations with powder distributions of a $d_{50} = 3$
508 mm. Note that large differences are observed in the number of granules used for each
509 experiment due to the different degrees of dispersion. While for a GSD with $\sigma_{geo} = 2$
510 the hopper was completely filled with 88000 granules, for $\sigma_{geo} = 1$ a total number of
511 504000 granules was required. All plots of figure 16 are equivalent and [the number of](#)
512 [granules and its dispersion](#) does not change the fact that the LIGGGHTS code is the
513 one that works best, followed by the CPU and GPU code. The order of complexity
514 of the algorithms is, for each case, linear with respect to the number of granules.

515 [The differences observed in calculation speed of each simulation are mainly at-](#)
516 [tributed to the large differences in the number of granules in each experiment.](#) Like-

517 wise, the differences between the three algorithms are reduced with the decrease in
518 the number of granules.

519 Regarding to the GPU code, in figure 16(a) the maximum difference observed
520 between the GPU code and the LIGGGHTS one is approximately 300 ms, while in
521 figure 16(d) the difference is only about 20ms. As discussed in Section 3.3, issues
522 such as code divergence, memory allocation, and too complex threads penalize the
523 GPU code.

524 4.2.2. Group B

525 Figure 17 illustrates the average elapsed time per iteration for a given number of
526 contacts in different simulations with powder distributions of $d_{50} = 0.5$ mm. These
527 GSD are similar to the true distribution of spray-dried powder used in the ceramic
528 tile industry [53]. The results shown here are hence of great relevance.

529 In these cases, the d_{50} is so small that in none of the simulations of group B it
530 was computationally possible to fill the hopper completely, because of the time that
531 would be required to complete the calculations (more than 10 million granules would
532 be involved). Consequently, a number of granules around 1 million was considered
533 sufficient to evaluate the code. This enabled all the calculations to be completed in
534 a reasonable time. [It is important to mention that the differences in the number of](#)
535 [granules used in these simulations were negligible. This statement was confirmed by](#)
536 [carrying out complementary performance analyses using exactly the same number of](#)
537 [granules \(1 million\).](#)

538 As in group A, the order of complexity of the algorithms is, for each case, linear
539 with respect to the number of granules. Figure 17 shows that code developed for
540 CPUs outperforms the code developed for GPUs, even more so than the LIGGGHTS
541 code. These differences are reduced by increasing σ_{geo} . It is remarkable that the

542 simulation with a value of $\sigma_{\text{geo}} = 1$ (figure 17(a)) could only be done with the CPU
543 code, since the RAM memory needed to run the simulation on the other two codes
544 was larger than that available. Table 3 provides the maximum RAM consumption
545 of each simulation shown in figure 17. It highlights the limitation of using a single
546 GPU in DEM simulation, due to the amount of RAM available. It also demonstrates
547 the bigger amount of RAM required by the LIGGGHTS code, since equipment with
548 which the simulations have been performed has 32GB of RAM (table A.1). Regarding
549 the other simulations (figures 17(b), 17(c), 17(d)), it was possible to perform them
550 without any trouble.

551 Memory availability is specially important in the LIGGGHTS code, since it is
552 required to explicitly define a calculation domain and store information of all the
553 cells present in it. This implies that the smaller the size of the cells and the larger
554 the domain, the more memory is required. In contrast, in the CPU and GPU codes,
555 the impact is much smaller, as the domain is not fully indexed, and the size of the
556 cells only influences the construction of the contact identification array A3 (figure 7).

557 On the other hand, as σ_{geo} increases, the default cell size of LIGGGHTS increases.
558 This involves two phenomena: (i) RAM consumption decreases. (ii) The number of
559 contacts per cell increases, so the resolution tends to $\mathcal{O}(n^2)$. Here, the increment leads
560 to a drastic reduction in memory consumption, and a substantial improvement in the
561 speed of the algorithm is observed. Therefore, the impact of memory management
562 on LIGGGHTS performance is greater than the impact of increasing σ_{geo} , even if it
563 means an increment of the number of evaluations of possible contacts per cell.

564 This pattern is shown in figure 18, where the slope of the trend lines drawn in
565 figure 17 is plotted as a function of the value of σ_{geo} . The impact of σ_{geo} on the
566 scalability of the codes developed is very low. However, the impact on LIGGGHTS
567 is very important.

568 *4.2.3. Discussion*

569 Simulations performance exhibits large differences depending on the number of
570 contacts involved. While in the simulations of the group A the LIGGGHTS code
571 is superior, in the simulations of the group B the CPU and GPU codes overper-
572 form LIGGGHTS. RAM consumption seems to be decisive for LIGGGHTS code
573 performance, as observed in table 3, where the enormous difference in memory con-
574 sumption of the algorithms is evidenced. Although this indicator alone does not
575 determine the quality of the algorithm, excessive memory use can expose problems
576 in its management, such as cache conflicts [54] and fragmentation [55].

577 With respect to GPU code, the results generally show much lower memory con-
578 sumption than LIGGGHTS code, but on the order of 4 times higher than CPU code.
579 This is due to the singular data structure used in GPU code, which needs to store
580 and replicate information in memory due to the limitations of the architecture. Note
581 here the huge advantage of the simulation algorithm developed over the one used
582 by LIGGGHTS, since with the available RAM in the GPU (5Gb), the possibilities
583 of the LIGGGHTS resolution scheme in this architecture would be really restrictive.
584 In both developed codes, the reduction of memory with the increased dispersion is
585 attributable to the reduction in the size of the array A3.

586 Finally, most of the results shown in figure 17 have hysteresis, specially the
587 LIGGGHTS and GPU code. This indicates that for the same number of contacts
588 there are parts of the calculation where the algorithm performance is different. The
589 explanation for this hysteresis is shown in figure 19. This figure shows the typical
590 evolution of the number of contacts in the simulations of the group B. In all the sub-
591 figures there are two differentiated areas where the number of contacts is extremely
592 high, corresponding to the filling of the feeder and to the moment when all the gran-

ules are on the mould. In figure 19(a) the different regions of the curve are associated
with the instant of filling shown in figure 15.

The first zone (between iteration $80 \cdot 10^3$ and $300 \cdot 10^3$ for figure 19(a)) corresponds
to the values of the upper part of the hysteresis in figures 17(b), 17(c) and 17(d). The
second zone (between iteration $400 \cdot 10^3$ and $600 \cdot 10^3$ for the figure 19(a)) corresponds
to the lower part of the hysteresis. The explanation of hysteresis may be related to
memory management. The continuous increase of the number of contacts in the
first zone necessarily involves a continuous memory allocation, while in the second
zone the information can simply be reallocated. Therefore, in the second part of
the simulation there would be no such over-cost and there is a greater probability of
memory access optimization. This behaviour is more difficult to observe in the CPU
code. In the first place, in this code the contacts are not stored in a single container,
so the optimization in the memory access is not so evident. Secondly, the CPU code
has a much lower RAM consumption than the other two, so the problems associated
with memory management are less visible.

As a general summary, figure 20 shows the average calculation time per iteration
as a function of the number of granules. Each algorithm and all the simulations
carried out have been included with the exception of figure 19(a), whose execution
was, considering our hardware, only feasible with the CPU code.

Considering all simulations, the order of complexity of the CPU and GPU codes
remains linear, while the LIGGGHTS code shows a fairly exponential one. For
scenarios with a low number of granules ($< 0.5 \cdot 10^6$) the LIGGGHTS code performs
better than those developed. In scenarios with a higher number of granules ($> 0.5 \cdot$
 10^6), the CPU code outperforms all others. GPU code is also faster than LIGGGHTS
when the number of granules is greater than $0.9 \cdot 10^6$ and small ($d_{50} = 0.5$ mm).

Finally, it is worth mentioning that the performance of the GPU code is not

619 as expected. On the one hand, although the parallelization capacity of the GPU
620 architecture is excellent, the data has to be processed carefully. A lot of intermedi-
621 ate stages are required to perform efficiently DEM simulations on GPU, hence the
622 code results less clean and comprehensible than the CPU one. On the other hand, al-
623 though it can be minimized, DEM simulations involve some divergence and may cause
624 memory bank conflicts in its execution. This is the case during the heterogeneous
625 contact evaluation (different element types in contact have different mathematical
626 treatment, the elements to evaluate are not necessarily adjacent in memory, etc.)
627 and the searching of the previous contact history, amongst others. Unfortunately,
628 GPU computing has an important performance penalty in those situations [56, 57].

629 On the other hand, in all cases the CPU code is faster than the GPU code.
630 This differences are more noticeable as the number of granules increases. As a last
631 remark, it is important to note that the conclusions drawn in figure 20 are subject
632 to the cases tested in this work, and the software and hardware conditions used.
633 Therefore, the conclusions are not necessarily extrapolated to other scenarios (for
634 example, to scenarios where, despite the number of granules, the number of cells
635 in the domain is not large enough to significantly increase RAM consumption) and
636 other computer equipment.

637 5. Conclusions

638 This paper presents two algorithms that overcome the restrictions of the tradi-
639 tional DEM resolution algorithm (based on a linked-list approach). The former is
640 aimed to be used on a multi-core CPU, and the latter in a single GPU. Both al-
641 gorithms make an efficient use of the available RAM on the system, and are not
642 limited by the domain calculation size. The proposed algorithms are a modified and
643 extended version of the algorithm proposed by Mazhar et al. [26]. Both codes have

644 been compared with the reference software LIGGGHTS by means of simulating a
645 mould filling as performed in ceramic tile manufacturing.

646 Regarding to the LIGGGHTS code, a direct relationship between the memory
647 consumption of LIGGGHTS (table 3) and its performance has been observed. In-
648 deed, the high computational cost of LIGGGHTS code in some situations is at-
649 tributed to management issues that can occur when RAM memory consumption is
650 so high. Although it has not been studied, it would be possible to increase the cell
651 size in the LIGGGHTS code in those simulations with higher memory consumption.
652 This would mean decreasing RAM memory consumption, although it would also
653 imply an increase in the number of granules in each cell (with the increase in the
654 number of evaluations that this involves). A previous study should be perform to
655 identify the optimal cell size.

656 With respect to the GPU code, the following conclusions have been reached:

- 657 • RAM limitation is a significant handicap of using a single GPU for DEM sim-
658 ulations. This drawback might be overcome by using a multi-GPU platform or
659 a CPU-GPU hybrid computation.
- 660 • Contact identification is much more complex to do on a GPU than on a CPU,
661 involving extra steps and making the code much less maintainable and readable.
- 662 • Despite using a high-performance graphics card (Kepler K20c), the developed
663 code for a single GPU performs significantly worse than the two CPU-based
664 codes analysed. It must be highlighted that the calculations always used
665 double-precision floating-point format and the granular system was formed by
666 a polydisperse size assembly of particles, where contact history is accurately
667 tracked for an arbitrary number of contacts. These aspects penalize tremen-
668 dously the GPU performance.

669 The conclusions reached concerning the CPU code are as follows:

- 670 • CPU code has proven to be the most versatile and balanced of the three codes.
- 671 • It is efficient for simulating both large and small quantities of granules.
- 672 • Its performance is markedly superior to the other codes when the number of
673 granules to be simulated is high, as in industrial scenarios.
- 674 • Its low memory consumption allows to run demanding simulations in conven-
675 tional computers without a high memory capacity.

676 According to the findings of this work, the CPU-based solver developed in this
677 research will be used in Part III of this collection to validate and study the spray-
678 dried powder model in a real filling system commonly used by the ceramic industry.
679 The validation process will be performed by comparing the model predictions with
680 the experimental results obtained from a prototype.

681 As final remark, it has been proven that the GPU architecture does not necessarily
682 outperforms the CPU one when implementing DEM. This findings agree with the
683 results of Lee et al. [23], Shigeto et al. [22] and Washizawa et al. [38]. However, Gan
684 et al.[32] also showed that the use of a single GPU does seem adequate to simulate
685 a maximum of about 1 million mono-sized and/or ellipsoidal particles.

686 In the author's opinion, the computational cost of simulating fine powders by
687 using spheres in DEM is not necessarily lower on a single GPU than on a multi-core
688 CPU. The extension of Mazhar's algorithm presented in this paper is a general-
689 purpose algorithm that handles efficiently typical spray-dried powders used in ce-
690 ramic tile industry. This extended algorithm enables the use of complex models that
691 require double precision calculations and tracking of the contact history. Further-
692 more, the purposed code architecture does not rely on predefined threshold values

693 to setup the optimum functioning of the solver. If a high-performance equipment is
694 not available and a solver that requires predefined values to adjust its functioning
695 is not desired, this research suggests that there are not substantial reasons to use a
696 single GPU computing platform to run powder simulations with DEM.

697 **6. Acknowledgements**

698 The authors of this paper wish to thank MACER S.L and the CDTI Ministry of
699 Science and Innovation of Spain, as part of the project with the reference number:
700 IDI20140989. J.M. Tiscar wishes to thank the Conselleria de Cultura, Educació i
701 Ciència de la Generalitat Valenciana for its financial support in the conducted study
702 with a PhD scholarship, through the programme VALi+D for researchers training.

703 **Appendix A. Equipment and programming specifications**

704 Table A.1 shows the hardware and software specifications for the simulations.
705 The total numbers of CPU parallel threads used in the simulations performed with
706 the CPU and LIGGGHTS code was 8. Furthermore, the domain in LIGGGHTS
707 was divided along the z-axis into 8 portions. This ensured that no thread was
708 idle. Regarding the GPU code, the simulations were performed launching parallel
709 thread blocks of 256 threads each of them. The number of blocks used depended
710 on the parallel threads required. All calculations were performed in double-precision
711 floating-point format.

712 The codes were written taking advantage of an object-oriented programming
713 (OOP) approach and mechanisms of Run-Time Type Information (RTTI) when pos-
714 sible. OOP is a programming language model that organizes software design around
715 data, or objects, rather than functions and logic. On the other hand, RTTI is a

716 mechanism that exposes information about an object's data type at runtime. It
717 provides a way to write cleaner code at the expense of an overhead. Unfortunately,
718 GPU programming still has much work to do with respect to the implementation
719 capabilities for OOP and RTTI. Although a procedural programming approach may
720 be more appropriate to perform High Performance Computing (HPC) [58], OOP in-
721 volves a natural implementation structure (easy to debug and maintain) which does
722 not compromise excessively the efficiency and feasibility of the code.

723 References

- 724 [1] P. A. Cundall, O. D. L. Strack, A discrete numerical model for granular assem-
725 bles, 1979.
- 726 [2] Z. Zhang, L. Liu, Y. Yuan, A. Yu, A simulation study of the effects of dynamic
727 variables on the packing of spheres, Powder Technology 116 (2001) 23–32.
- 728 [3] C. Bierwisch, T. Kraft, H. Riedel, M. Moseler, Die filling optimization using
729 three-dimensional discrete element modeling, Powder Technology 196 (2009)
730 169–179.
- 731 [4] Y. Guo, C.-Y. Wu, K. Kafui, C. Thornton, 3D DEM/CFD analysis of size-
732 induced segregation during die filling, Powder Technology 206 (2011) 177–188.
- 733 [5] Y. Tsunazawa, Y. Shigeto, C. Tokoro, M. Sakai, Numerical simulation of in-
734 dustrial die filling using the discrete element method, Chemical Engineering
735 Science 138 (2015) 791–809.
- 736 [6] S. Luding, Collisions & Contacts between two particles, Physics of dry granular
737 media - NATO ASI Series E350 1 (1998) 285.

- 738 [7] H. Hertz, On the contact of elastic solids, *Journal für die reine und angewandte*
739 *Mathematik* 92 (1881) 156–171.
- 740 [8] K. L. Johnson, *Contact Mechanics*, Cambridge University Press, 1985. Cam-
741 *bridge Books Online*.
- 742 [9] S. Kozhar, M. Dosta, S. Antonyuk, S. Heinrich, U. Bröckel, DEM simulations
743 of amorphous irregular shaped micrometer-sized titania agglomerates at com-
744 pression, *Advanced Powder Technology* 26 (2015) 767–777.
- 745 [10] B. An, D. D. Tannant, Discrete element method contact model for dynamic
746 simulation of inelastic rock impact, *Computers & Geosciences* 33 (2007) 513 –
747 521.
- 748 [11] M. Sakai, S. Koshizuka, Large-scale discrete element modeling in pneumatic
749 conveying, *Chemical Engineering Science* 64 (2009) 533–539.
- 750 [12] CFDEM[®] Project, LIGGGHTS – Open-Source Discrete Element Simulations of
751 Granular Materials Based on LAMMPS. Documentation. Versión 3.X, <https://www.cfdem.com/media/DEM/docu/Manual.html>, 2020.
752
- 753 [13] LAMMPS molecular dynamics package, <http://lammps.sandia.gov>, 2016.
- 754 [14] M. P. Allen, D. J. Tildesley, *Computer Simulation of Liquids*, Clarendon Press,
755 1989.
- 756 [15] J.-A. Ferrez, T. M. Liebling, High-Performance Computing and Networking: 9th
757 International Conference, HPCN Europe 2001 Amsterdam, The Netherlands,
758 June 25–27, 2001 Proceedings, Springer Berlin Heidelberg, Berlin, Heidelberg,
759 pp. 211–220.

- 760 [16] H. Nguyen, Chapter 32. Broad-Phase Collision Detection with CUDA, Addison-
761 Wesley Professional, first edition, 2007.
- 762 [17] R. Couturier, Designing scientific applications on GPUs, CRC Press, 2013.
- 763 [18] L. Genovese, B. Videau, D. Caliste, J.-F. Méhaut, S. Goedecker, T. Deutsch,
764 Electronic Structure Calculations on Graphics Processing Units: From Quantum
765 Chemistry to Condensed Matter Physics, Wiley-Blackwell, 2016.
- 766 [19] J. R. Cheng, M. Gen, Accelerating genetic algorithms with GPU computing: A
767 selective overview, Computers & Industrial Engineering 128 (2019) 514 – 525.
- 768 [20] M. Durand, P. Marin, F. Faure, B. Raffin, DEM-based simulation of concrete
769 structures on GPU, European Journal of Environmental and Civil Engineering
770 16 (2012) 1102–1114.
- 771 [21] C. A. Radeke, B. J. Glasser, J. G. Khinast, Large-scale powder mixer simulations
772 using massively parallel GPU architectures, Chemical Engineering Science 65
773 (2010) 6435 – 6442.
- 774 [22] Y. Shigeto, M. Sakai, Parallel computing of discrete element method on multi-
775 core processors, Particuology 9 (2011) 398–405.
- 776 [23] V. Lee, C. Kim, J. Chhugani, M. Deisher, D. Kim, et al., Debunking the 100X
777 GPU vs. CPU myth: an evaluation of throughput computing on CPU and GPU,
778 ACM SIGARCH Computer Architecture News 38 (2010) 451–460.
- 779 [24] M. Xu, F. Chen, X. Liu, W. Ge, J. Li, Discrete particle simulation of gas-
780 solid two-phase flows with multi-scale CPU-GPU hybrid computation, Chemical
781 Engineering Journal 207-208 (2012) 746 – 757. 22nd International Symposium
782 on Chemical Reaction Engineering (ISCRE 22).

- 783 [25] Y. He, F. Muller, A. Hassanpour, A. E. Bayly, A CPU-GPU cross-platform
784 coupled CFD-DEM approach for complex particle-fluid flows, Chemical Engi-
785 neering Science 223 (2020) 115712.
- 786 [26] H. Mazhar, T. Heyn, D. Negrut, A scalable parallel method for large collision
787 detection problems, Multibody System Dynamics 26 (2011) 37–55.
- 788 [27] N. Govender, D. Wilke, S. Kok, A large scale discrete element framework for
789 NVIDIA GPUs, in: NVIDIA GTC 2015, California.
- 790 [28] N. Govender, R. K. Rajamani, S. Kok, D. N. Wilke, Discrete element simula-
791 tion of mill charge in 3D using the BLAZE-DEM GPU framework, Minerals
792 Engineering 79 (2015) 152–168.
- 793 [29] K. J. Bowers, D. E. Chow, H. Xu, R. O. Dror, M. P. Eastwood, B. A. Gregersen,
794 J. L. Klepeis, I. Kolossvary, M. A. Moraes, F. D. Sacerdoti, J. K. Salmon,
795 Y. Shan, D. E. Shaw, Scalable algorithms for molecular dynamics simulations on
796 commodity clusters, in: SC '06: Proceedings of the 2006 ACM/IEEE Conference
797 on Supercomputing, pp. 43–43.
- 798 [30] NVIDIA Corporation, NVIDIA CUDA Programming Guide version 7.5, http://docs.nvidia.com/cuda/pdf/CUDA_C_Programming_Guide.pdf, 2015. Ac-
799 cessed: 2016-05-04.
- 801 [31] J. Zheng, X. An, M. Huang, GPU-based parallel algorithm for particle con-
802 tact detection and its application in self-compacting concrete flow simulations,
803 Computers and Structures 112-113 (2012) 193–204.
- 804 [32] J. Gan, Z. Zhou, A. Yu, A GPU-based DEM approach for modelling of partic-
805 ulate systems, Powder Technology 301 (2016) 1172 – 1182.

- 806 [33] D. Nishiura, H. Sakaguchi, Parallel-vector algorithms for particle simulations on
807 shared-memory multiprocessors, *Journal of Computational Physics* 230 (2011)
808 1923–1938.
- 809 [34] D. Nishiura, M. Furuichi, H. Sakaguchi, Computational performance of a
810 smoothed particle hydrodynamics simulation for shared-memory parallel com-
811 puting, *Computer Physics Communications* 194 (2015) 18 – 32.
- 812 [35] J. Gan, T. Evans, A. Yu, Application of GPU-DEM simulation on large-scale
813 granular handling and processing in ironmaking related industries, *Powder Tech-
814 nology* 361 (2020) 258 – 273.
- 815 [36] S. Ji, L. Liu, High Performance Algorithm and Computing Analysis Software
816 of DEM Based on GPU Parallel Algorithm, Springer Singapore, Singapore, pp.
817 211–234.
- 818 [37] J. Fang, H. Sips, L. Zhang, C. Xu, Y. Che, et al., Test-driving Intel® Xeon
819 Phi, in: *Proceedings of the 5th ACM/SPEC International Conference on Per-
820 formance Engineering*, ACM, pp. 137–148.
- 821 [38] T. Washizawa, Y. Nakahara, Parallel Computing of Discrete Element Method
822 on GPU, *Applied Mathematics* 4 (2013) 242–247.
- 823 [39] J. K. Hahn, Realistic animation of rigid bodies, *Proceedings of the 15th Annual
824 Conference on Computer Graphics and Interactive Techniques, SIGGRAPH
825 1988* 22 (1988) 299–308.
- 826 [40] B. Mirtich, Efficient algorithms for two-phase collision detection, *Practical
827 Motion Planning in Robotics Current Approaches and Future Directions* (1997)
828 203–223.

- 829 [41] H. Samet, An Overview of Quadtrees, Octrees, and Related Hierarchical Data
830 Structures, Theoretical Foundations of Computer Graphics and CAD (1988)
831 51–68.
- 832 [42] H. Mio, A. Shimosaka, Y. Shirakawa, J. Hidaka, Cell optimization for fast
833 contact detection in the discrete element method algorithm, Advanced Powder
834 Technology 18 (2007) 441 – 453.
- 835 [43] J. Su, Z. Gu, X. Y. Xu, Discrete element simulation of particle flow in arbitrarily
836 complex geometries, Chemical Engineering Science 66 (2011) 6069–6088.
- 837 [44] A. Di Renzo, F. P. Di Maio, Comparison of contact-force models for the sim-
838 ulation of collisions in DEM-based granular flow codes, Chemical Engineering
839 Science 59 (2004) 525–541.
- 840 [45] D. Cohen, Voxel traversal along a 3D line , Graphics gems IV 4 (1994) 366.
- 841 [46] F. Dachille, A. Kaufman, Incremental Triangle Voxelization, in: Proceedings of
842 the Graphics Interface 2000 Conference, May 15-17, Montréal, Québec, Canada,
843 pp. 205–212.
- 844 [47] B. Peng, L. Wang, M. Abbas, C. Druta, Discrete Element Method (DEM)
845 Contact Models Applied to Pavement Simulation, Ph.D. thesis, 2014.
- 846 [48] P. Xiang, Y. Yang, H. Zhou, Warp-level divergence in gpus: Characterization,
847 impact, and mitigation, in: 2014 IEEE 20th International Symposium on High
848 Performance Computer Architecture (HPCA), pp. 284–295.
- 849 [49] L. Zhang, S. Quigley, A. Chan, A fast scalable implementation of the two-
850 dimensional triangular Discrete Element Method on a GPU platform, Adv.
851 Eng. Softw. 60-61 (2013) 70–80.

- 852 [50] M. Chimeh, P. Richmond, Simulating heterogeneous behaviours in complex
853 systems on GPUs, *Simul. Model. Pract. Th.* (2018).
- 854 [51] T. Liu, N. Wolfe, H. Lin, C. D. Carothers, X. G. Xu, Performance study
855 of atomic tally methods for gpu-accelerated monte carlo dose calculation, in:
856 20th Topical Meeting of the Radiation Protection and Shielding Division of the
857 American Nuclear Society.
- 858 [52] J. M. Tiscar, A. Escrig, G. Mallol, J. Boix, F. A. Gilabert, DEM-based modelling
859 framework for spray-dried powders in ceramic tiles industry. Part I: Calibration
860 procedure, *Powder Technology* 356 (2019) 818–831.
- 861 [53] J. Amorós, V. Bagan, M. Orts, A. Escardino, La operación de prensado en la
862 fabricación de pavimentos por monococción. I. Influencia de la naturaleza del
863 polvo de prensas sobre las propiedades de las piezas en crudo, *Bol. Soc. Esp.*
864 *Ceram. Vidr* 27 (1988) 273–282.
- 865 [54] Y. Afek, D. Dice, A. Morrison, Cache index-aware memory allocation, *ACM*
866 *SIGPLAN Notices* 46 (2011) 55–64.
- 867 [55] C. Walls, Dynamic Memory Allocation and Fragmentation in C & C++, in:
868 *Embedded World 2018*, Nuremberg.
- 869 [56] P. Xiang, Y. Yang, H. Zhou, Warp-level divergence in gpus: Characterization,
870 impact, and mitigation, in: *High Performance Computer Architecture (HPCA)*,
871 2014 IEEE 20th International Symposium on, IEEE, pp. 284–295.
- 872 [57] A. R. Brodtkorb, T. R. Hagen, M. L. Sætra, Graphics processing unit (gpu)
873 programming strategies and trends in gpu computing, *Journal of Parallel and*
874 *Distributed Computing* 73 (2013) 4 – 13. Metaheuristics on GPUs.

Please cite this article as:

J.M. Tiscar, A. Escrig, G. Mallol, J. Boix and F.A.Gilabert

"DEM-based modelling framework for spray-dried powders in ceramic tiles industry. Part II: Solver implementation".
Powder Technology (2020), DOI: 10.1016/j.powtec.2020.08.095

Received 4 May 2020, Revised 15 August 2020, Accepted 29 August 2020, Available online 6 September 2020.

- 875 [58] R. Balevičius, a. Džiugys, R. Kačianauskas, a. Maknickas, K. Vislavičius, In-
876 vestigation of performance of programming approaches and languages used for
877 numerical simulation of granular material by the discrete element method, Com-
878 puter Physics Communications 175 (2006) 404–415.

879 **Tables**

Table 1. Total of simulations in the performance analysis.

Label			GSD		Number of granules	$\Delta t(\mu s)$	Group
CPU	GPU	LIGGGHTS	$d_{50}(\text{mm})$	σ_{geo}			
A1-CPU	A1-GPU	A1-LIGGGHTS	3	1	504000	50	A
A2-CPU	A2-GPU	A2-LIGGGHTS	3	1.2	356000	50	
A3-CPU	A3-GPU	A3-LIGGGHTS	3	1.4	224000	50	
A4-CPU	A4-GPU	A4-LIGGGHTS	3	2	88000	50	
B1-CPU	B1-GPU	B1-LIGGGHTS	0.5	1	1316000	10	B
B2-CPU	B2-GPU	B2-LIGGGHTS	0.5	1.2	1122000	10	
B3-CPU	B3-GPU	B3-LIGGGHTS	0.5	1.4	946000	3	
B4-CPU	B4-GPU	B4-LIGGGHTS	0.5	2	1071100	3	

Table 2. Simulation parameters in the performance analysis.

Contact Granule-Granule	
Granule density, ρ_g (kg/m ³)	2000
Normal stiffness, k_n (N/m)	100
Tangential stiffness, k_s (N/m)	100
Rolling stiffness, k_r (N/m)	0
Damping normal, γ_n (kg·m/s)	0
Damping tangential, γ_s (kg·m/s)	0
Sliding friction, $\mu_{s,g-g}$	0.5
Rolling friction, $\mu_{r,g-g}$	0
Contact Granule-Boundary	
Granule density, ρ_g (kg/m ³)	2000
Normal stiffness, k_n (N/m)	200
Tangential stiffness, k_s (N/m)	200
Rolling stiffness, k_r (N/m)	0
Damping normal, γ_n (kg·m/s)	0
Damping tangential, γ_s (kg·m/s)	0
Sliding friction, $\mu_{s,g-s}$	0.5
Rolling friction, $\mu_{r,g-s}$	0
Hopper velocity (m/s)	0.1
Feeder velocity (m/s)	0.5

Table 3. Maximum RAM consumption (MB), in figure 17.

Group B $d_{50} = 0.5$ mm	CPU	LIGGGHTS	GPU
(a)	1070	-	-
(b)	1029	28534	4275
(c)	882	12175	3356
(d)	664	2835	2922

Table A.1. Hardware and software specifications for the simulations.

Specifications	
Operating System	Ubuntu 14.04
Processor	Intel® Xeon® E3-1234 v3 <ul style="list-style-type: none"> • Frequency: 3.4Ghz • Bandwidth: 25.6Gb/s • Cores: 4 • Threads: 8
RAM	32 Gb
Graphic Card	NVIDIA® Kepler K20c <ul style="list-style-type: none"> • Connection: PCI Express x16 • RAM: 5Gb • Bandwidth: 208Gb/s • Processor cores: 2496
CPU code parallelization	Shared memory parallel programming <ul style="list-style-type: none"> • Library: Intel® TBB
Compiling tools	<ul style="list-style-type: none"> • Programming Language: C++ • CPU: g++-4.8.4 with flag -Ofast • GPU: nvcc-7.5 with flag -Ofast • CUDA Toolkit 7.5

880 **Figures**

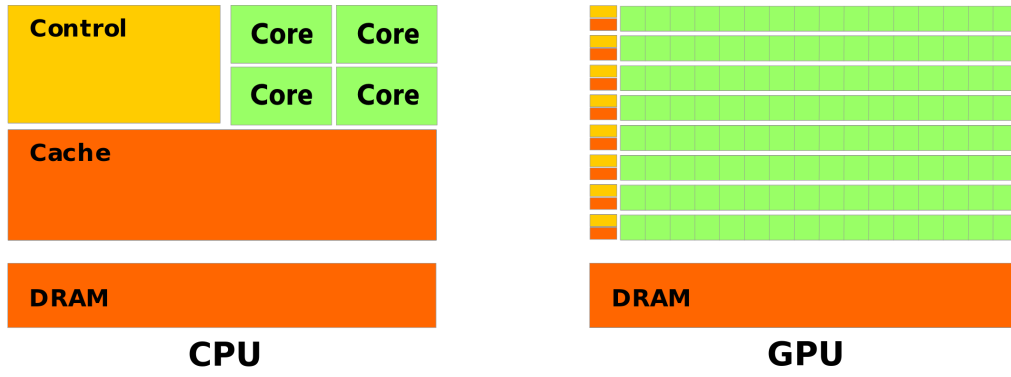


Fig. 1. Basic architecture differences between CPU and GPU.

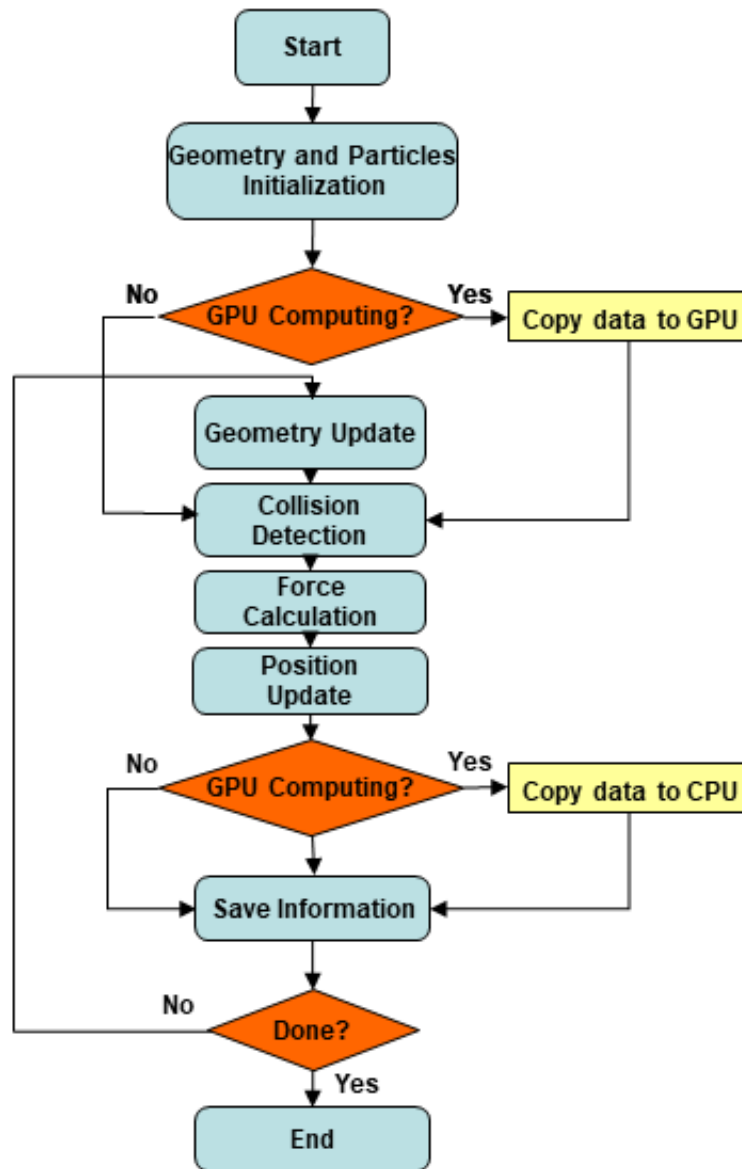


Fig. 2. The basic scheme of DEM simulations

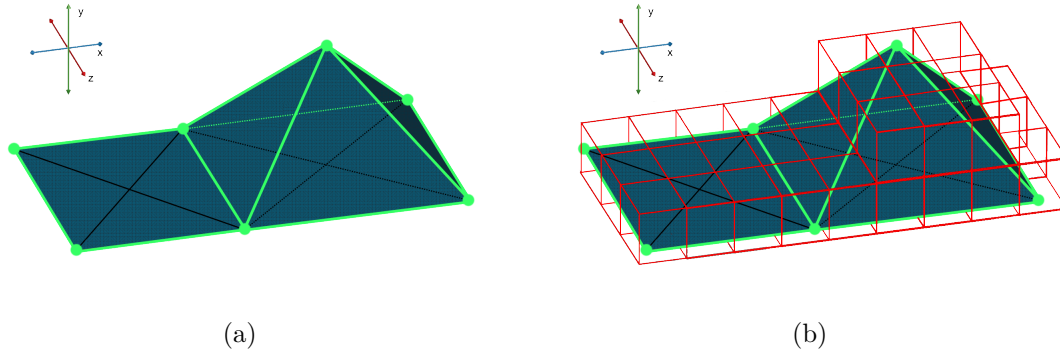


Fig. 3. Example of a geometry composed of a triangular mesh. Although all faces are considered, only the outer edges and vertices (green) are introduced into the model. (a) without grid. (b) with grid.

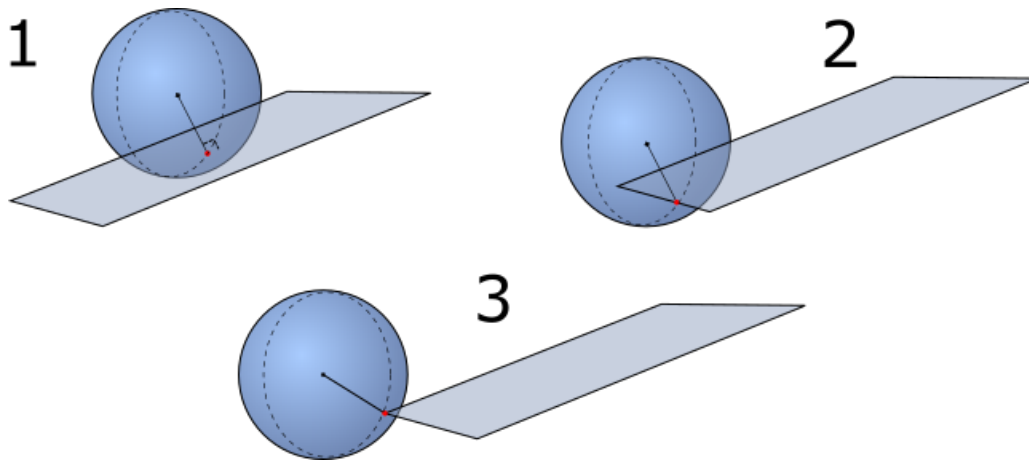


Fig. 4. Types of contact scenarios between the granules and the geometric elements.

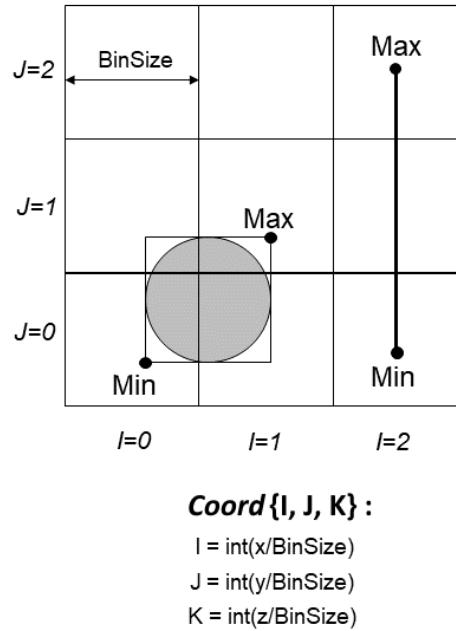


Fig. 5. Bounding box of different objects. A uniform spatial subdivision is used to normalize the coordinates.

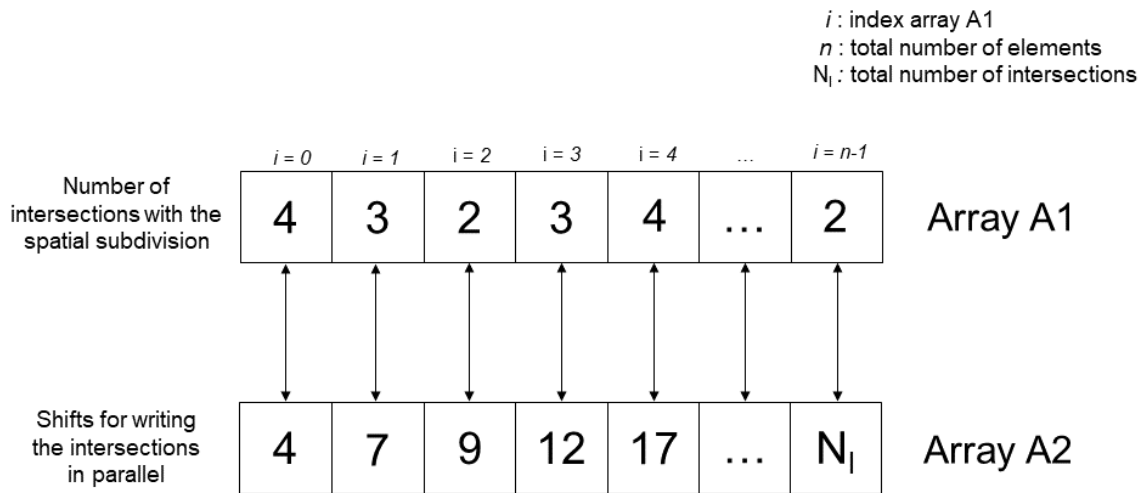


Fig. 6. Examples of Array A1 and A2. A1 results of intersection counting. A2 results of the partial summation performed on A1.

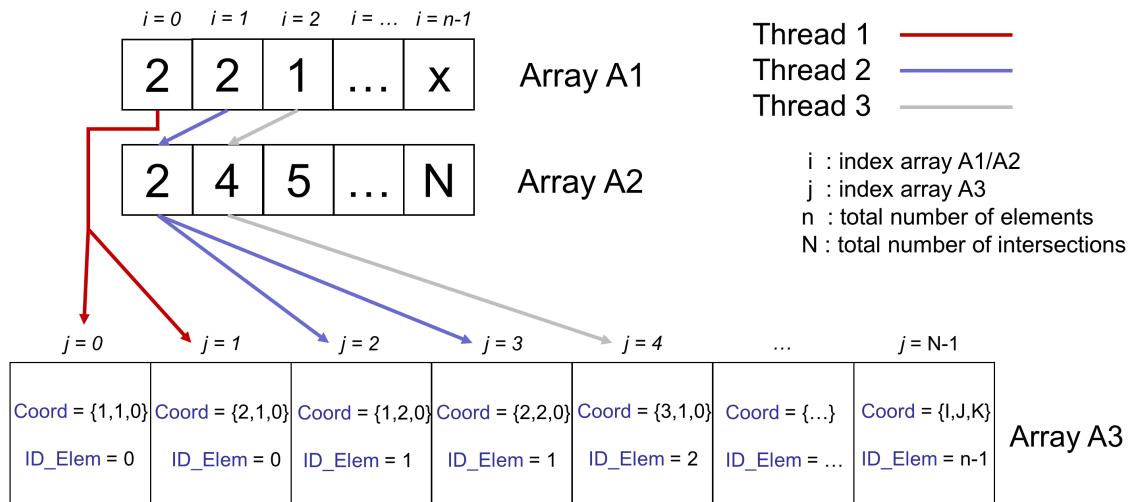


Fig. 7. Construction of array A3 in parallel, from arrays A1 and A2.

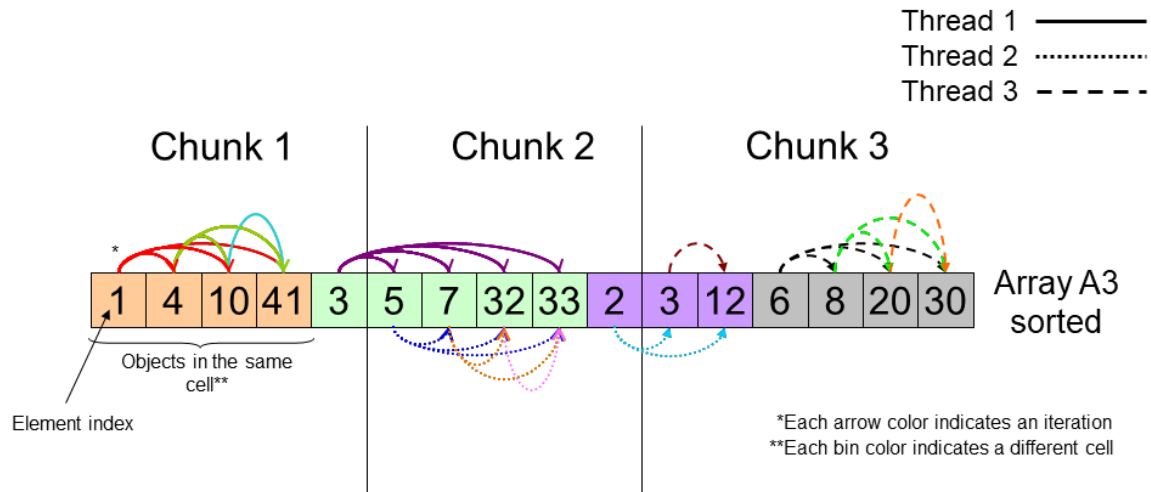


Fig. 8. (Color online) Schematic of how the contact evaluation works in array A3 sorted.

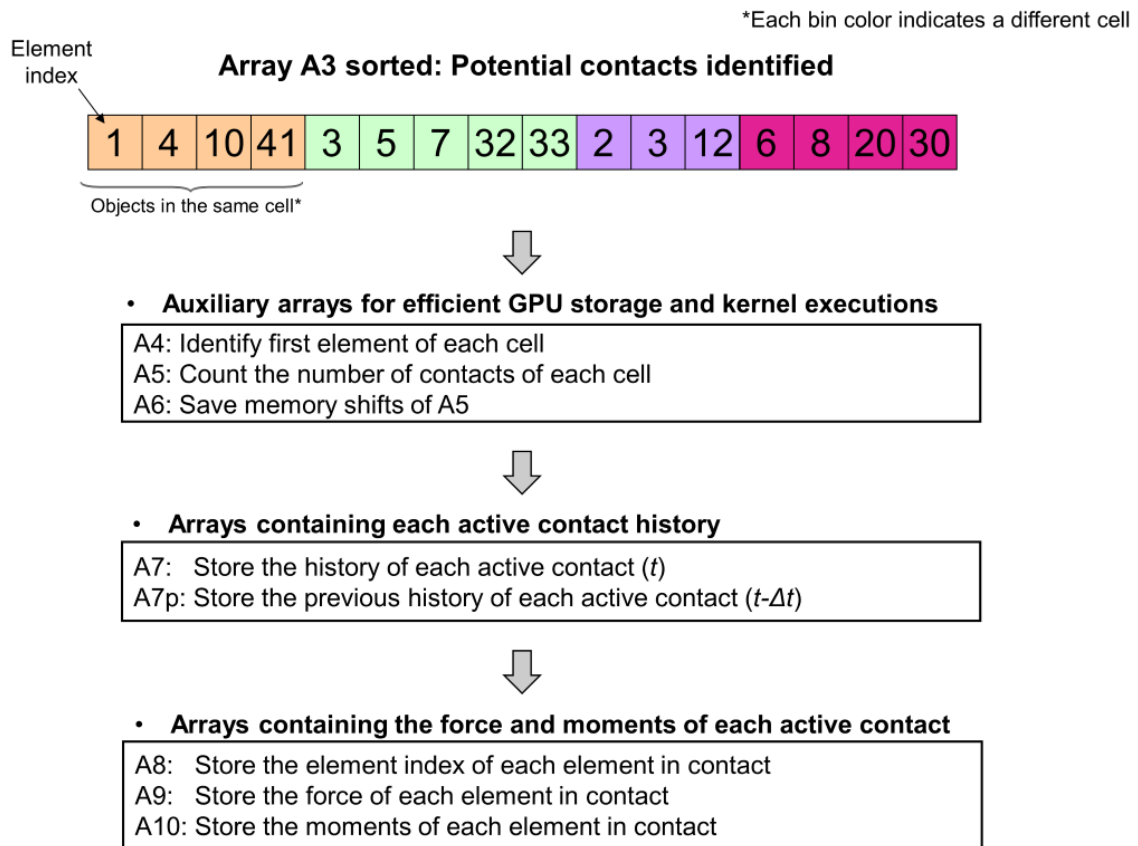


Fig. 9. Flowchart of the arrays created from A3, during the DEM algorithm on a GPU.

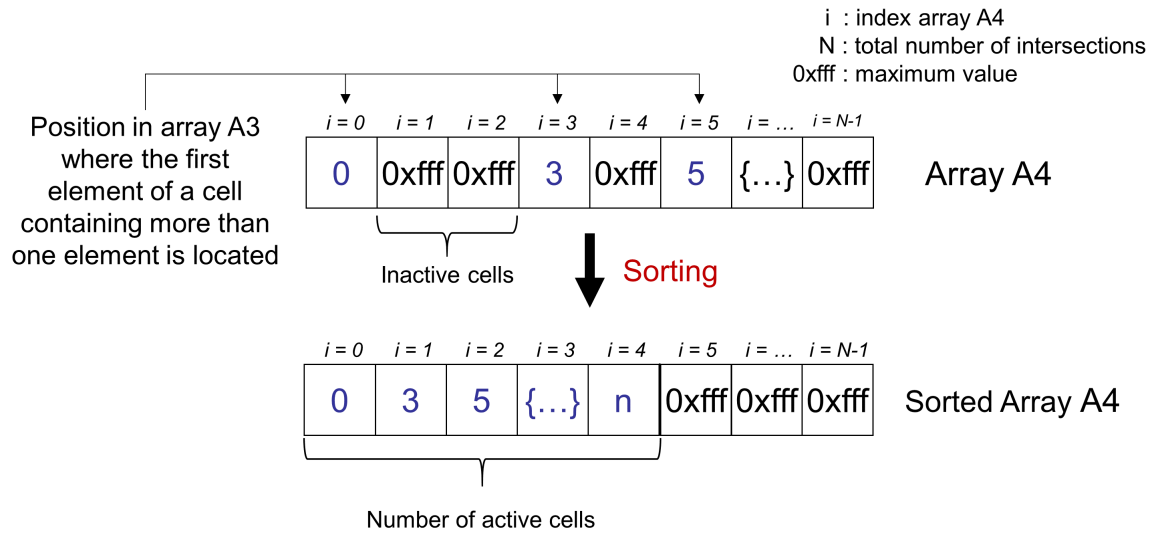


Fig. 10. Array A4 for the parallel evaluation of contacts.

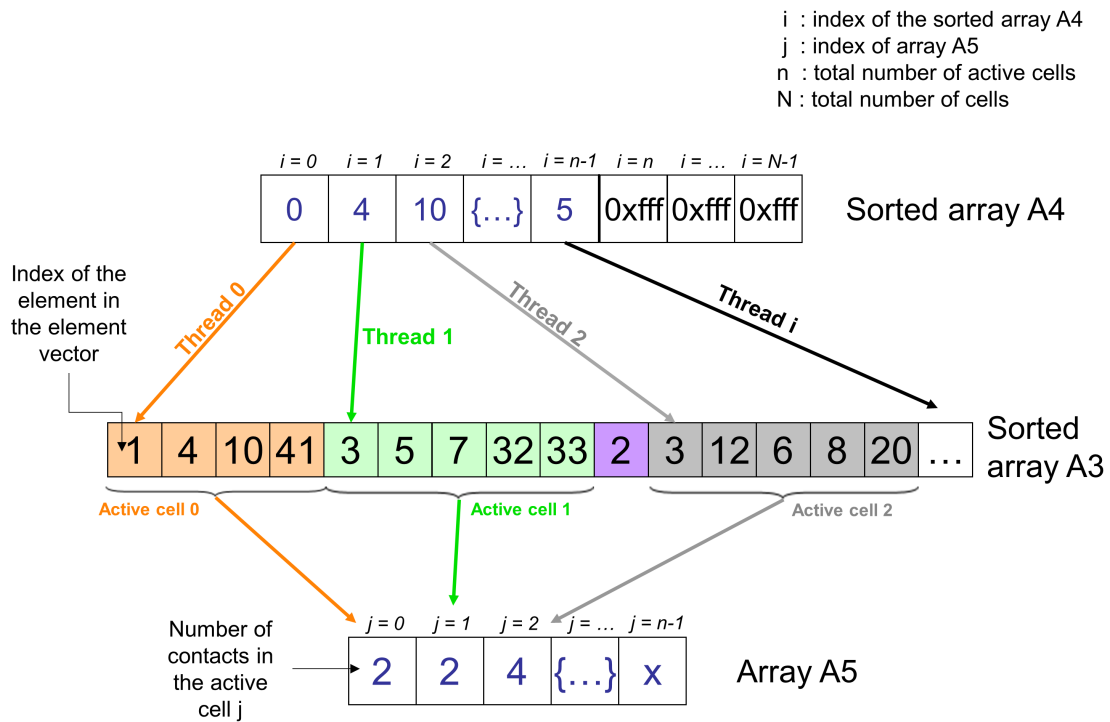


Fig. 11. Contact counting in the GPU algorithm.

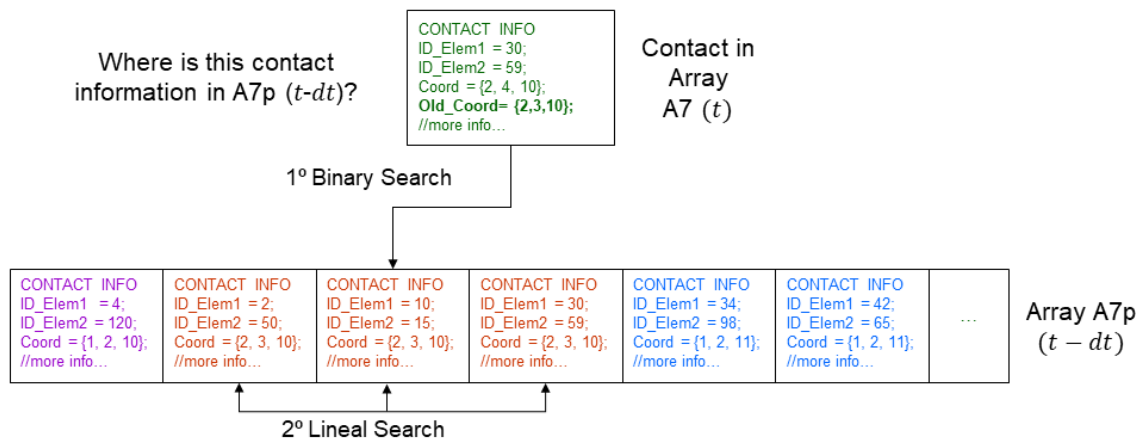


Fig. 12. Searching for a previous contact history.

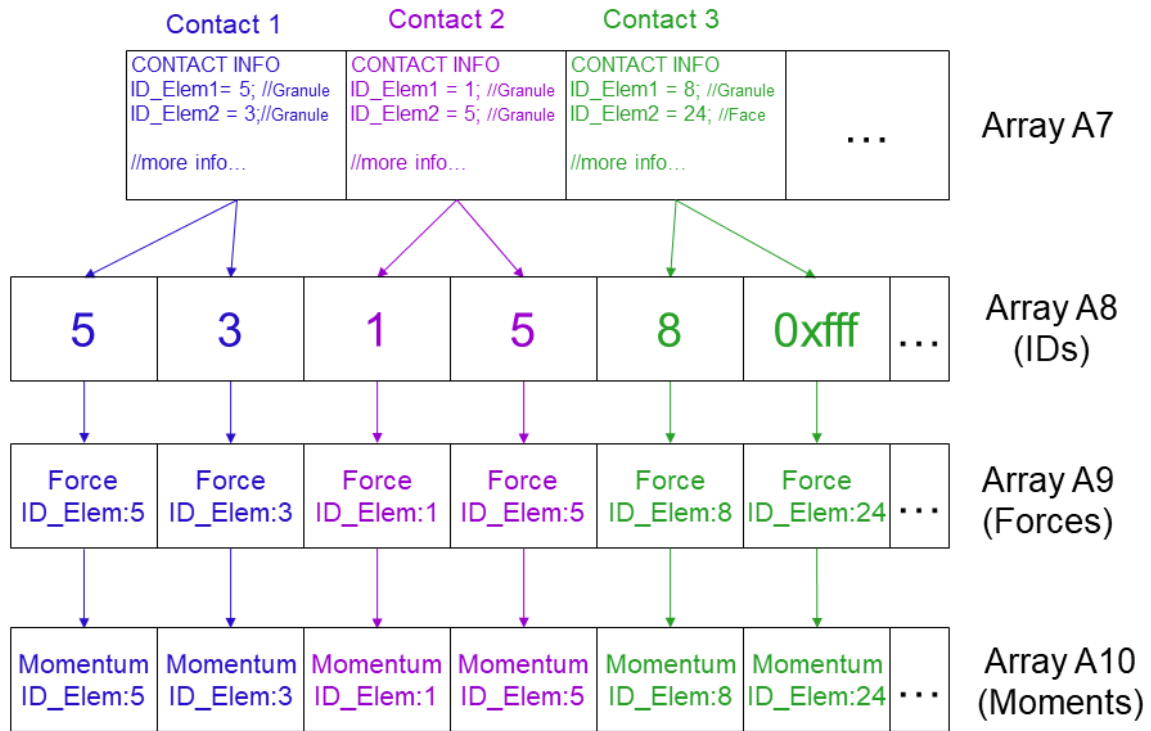


Fig. 13. Construction diagram of arrays A8, A9 and A10.

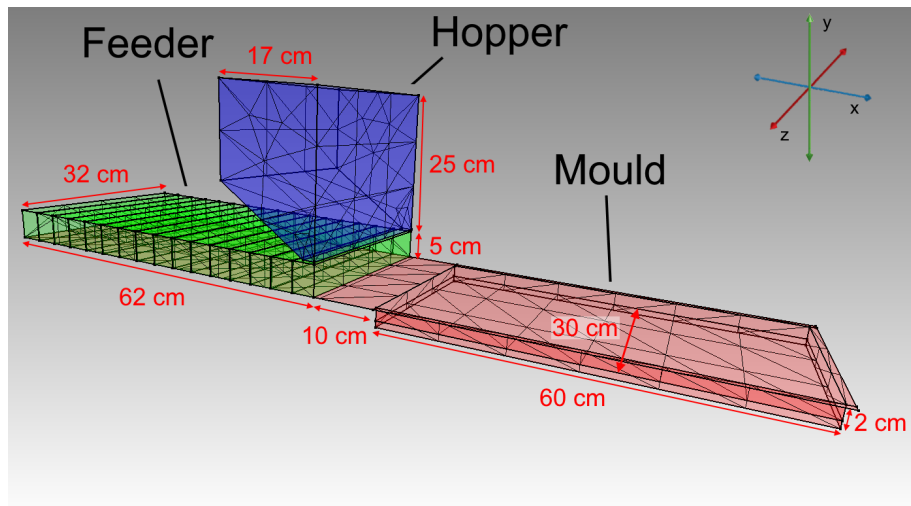


Fig. 14. Mould filling system used in the performance analysis.

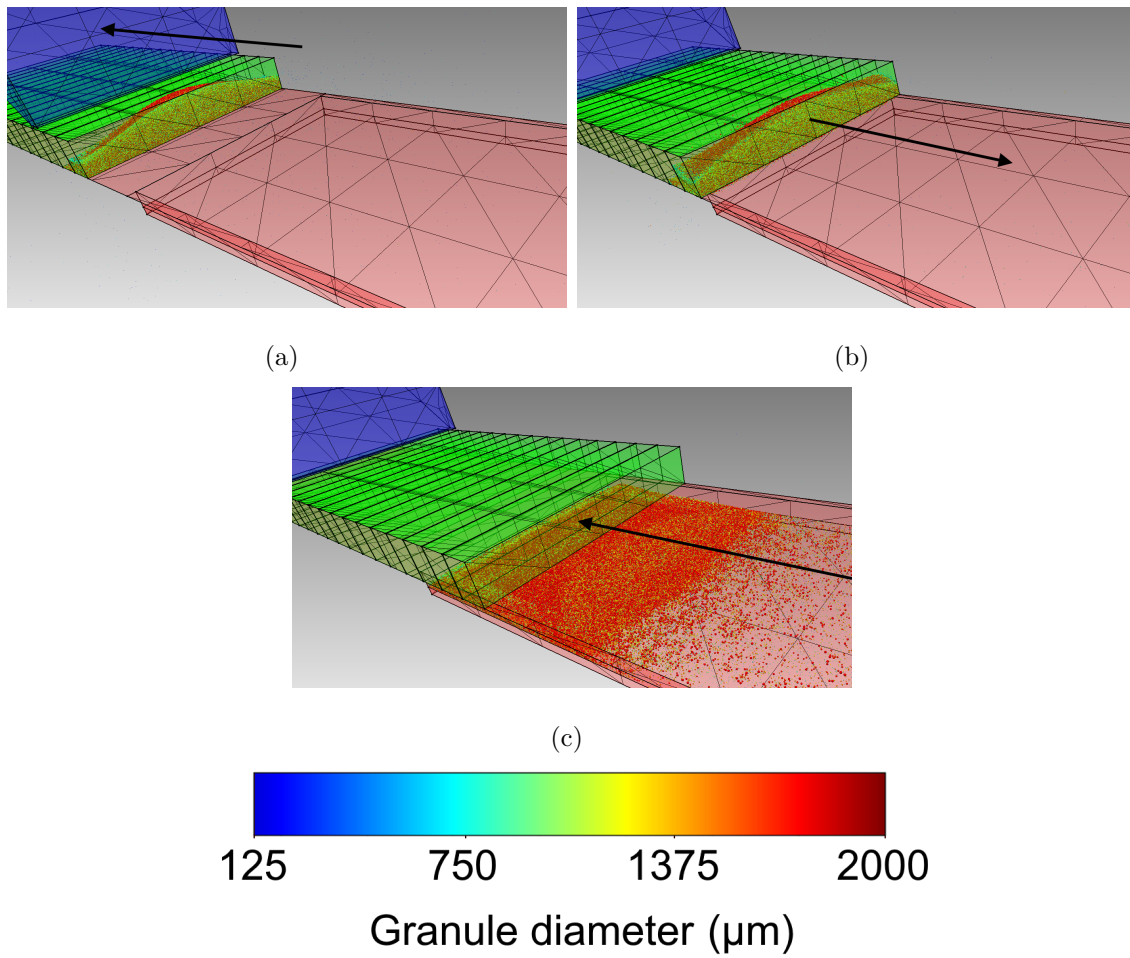
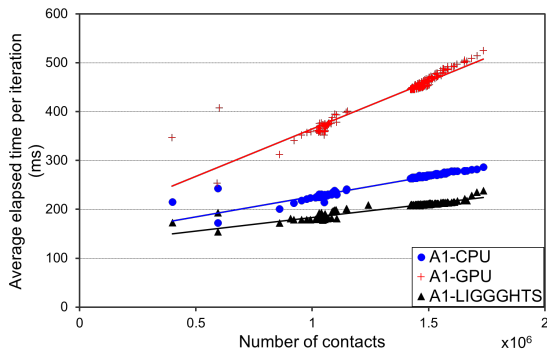
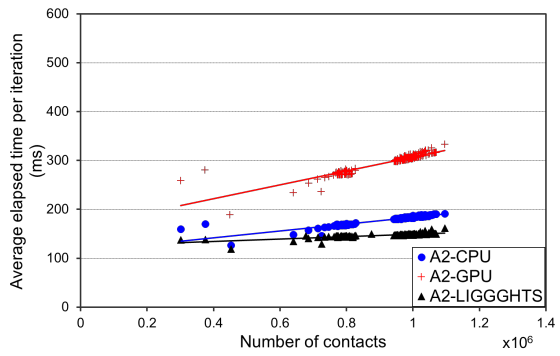


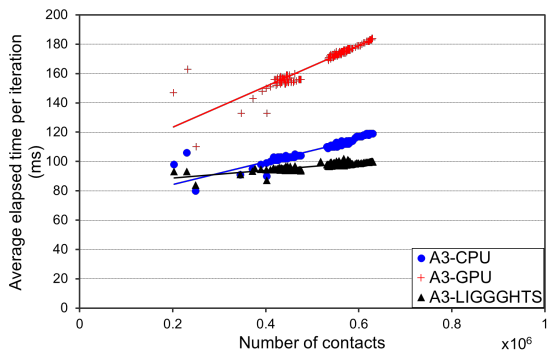
Fig. 15. Sequence of mould filling in the ceramic tile forming process. Simulation A4.



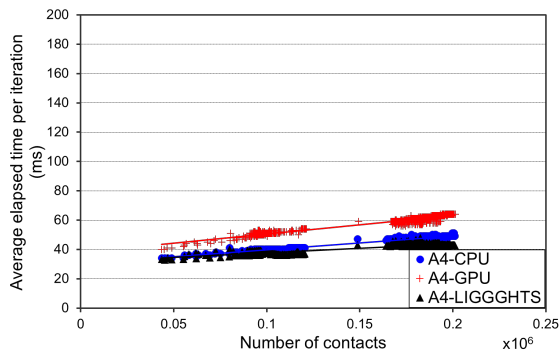
(a) $\sigma_{geo} = 1$, 504000 granules



(b) $\sigma_{geo} = 1.2$, 356000 granules

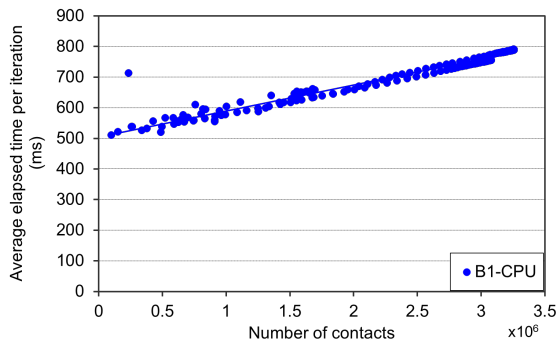


(c) $\sigma_{geo} = 1.4$, 224000 granules

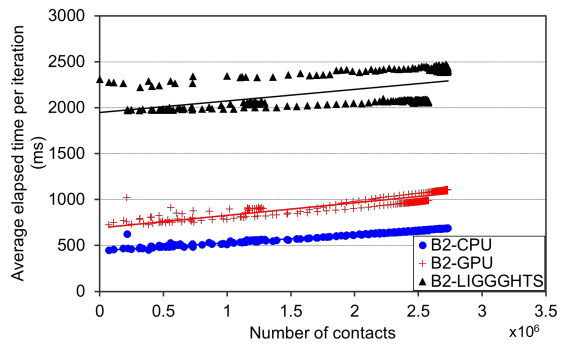


(d) $\sigma_{geo} = 2$, 88000 granules

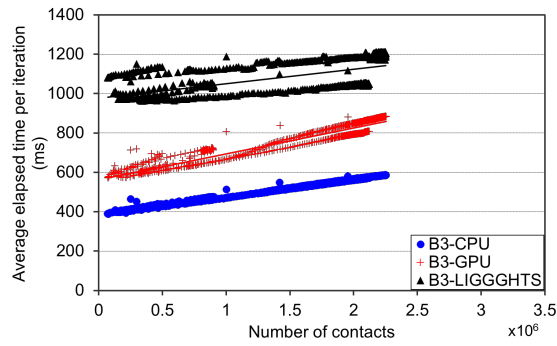
Fig. 16. Performance analysis of the group A ($d_{50} = 3\text{ mm}$).



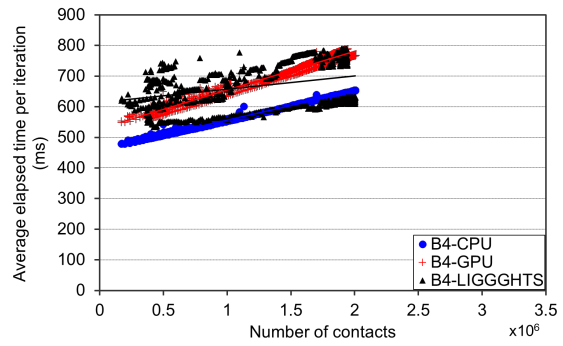
(a) $\sigma_{geo} = 1$, 1316000 granules



(b) $\sigma_{geo} = 1.2$, 1122000 granules



(c) $\sigma_{geo} = 1.4$, 946000 granules



(d) $\sigma_{geo} = 2$, 1071100 granules

Fig. 17. Performance analysis of the group B ($d_{50} = 0.5$ mm).

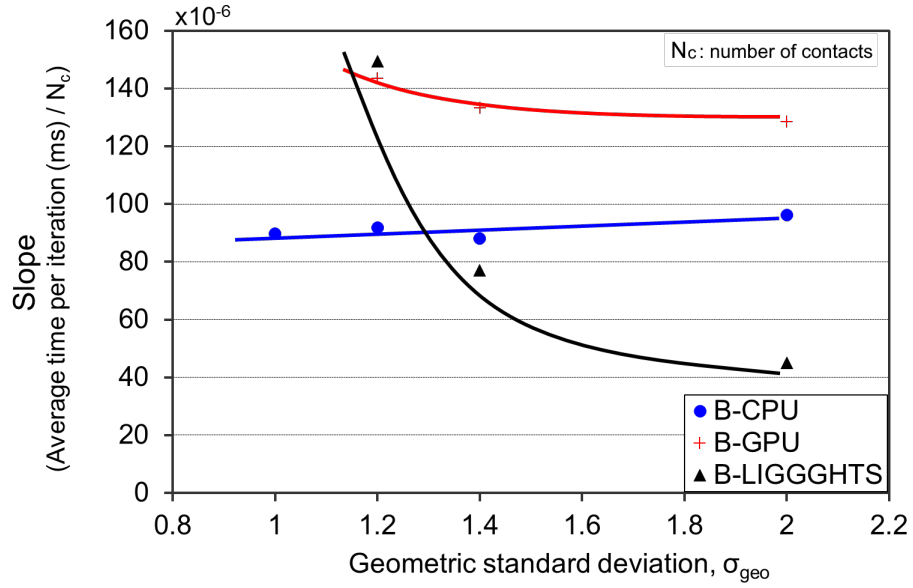


Fig. 18. The impact of σ_{geo} on the scalability based on figure 17.

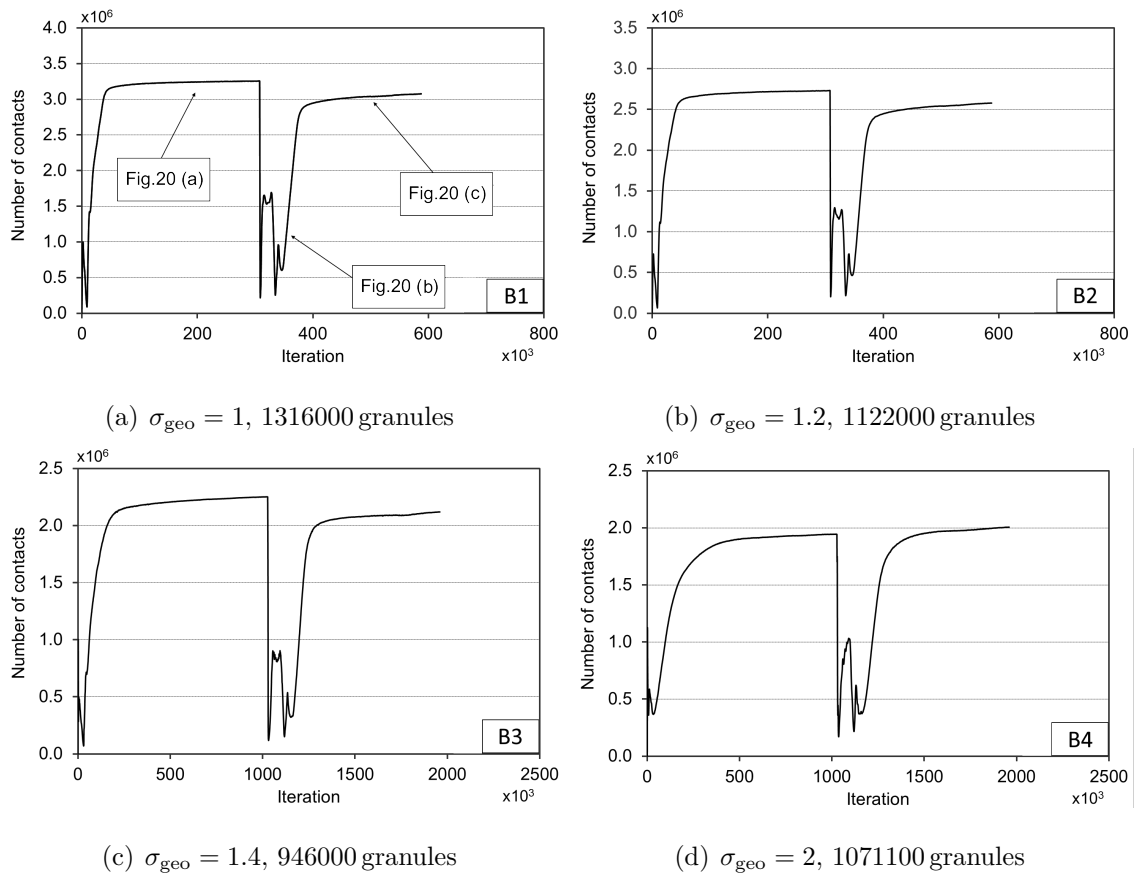


Fig. 19. Evolution of the number of contacts in the group B simulations.

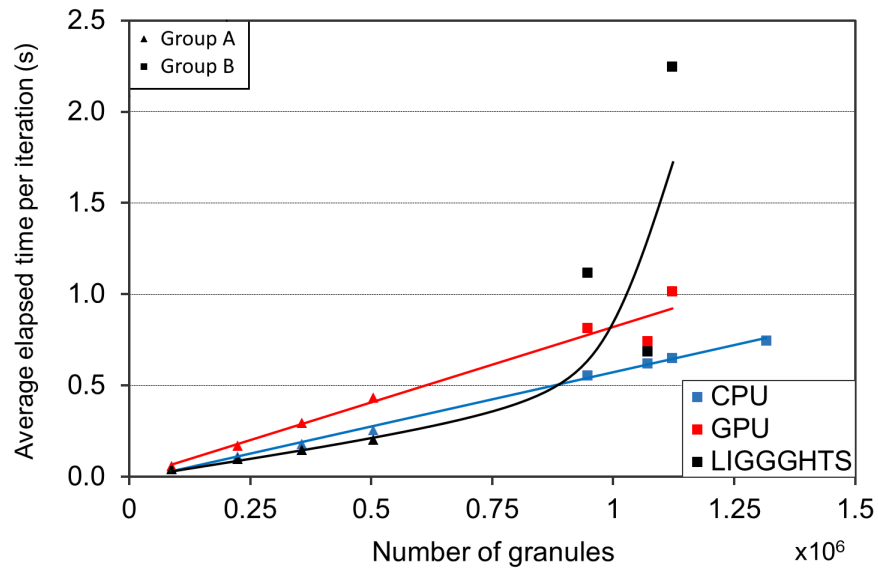


Fig. 20. Representation of the average calculation time per iteration as a function of the number of granules.

Please cite this article as:

J.M. Tiscar, A. Escrig, G. Mallol, J. Boix and F.A.Gilabert

"DEM-based modelling framework for spray-dried powders in ceramic tiles industry. Part II: Solver implementation".
Powder Technology (2020), DOI: 10.1016/j.powtec.2020.08.095

Received 4 May 2020, Revised 15 August 2020, Accepted 29 August 2020, Available online 6 September 2020.

881 Algorithms

Algorithm 1 Compute and assign forces and moments in parallel

Require:

- 1: G_i ▷ Granule i abstraction
- 2: G_j ▷ Granule j abstraction

Initialize:

- 3: $\mathbf{F} = \{F_x, F_y, F_z\}$ ▷ 3D Force
- 4: $\mathbf{M}_i = \{M_x, M_y, M_z\}$ ▷ 3D Moment on G_i
- 5: $\mathbf{M}_j = \{M_x, M_y, M_z\}$ ▷ 3D Moment on G_j

6: **if** not contact between granules **then**

7: **return**

8: **end if**

▷ Computation depending on the constitutive model

9: $\mathbf{F} \leftarrow$ Compute force between G_i and G_j

10: $\mathbf{M}_i \leftarrow$ Compute moment on G_i

11: $\mathbf{M}_j \leftarrow$ Compute moment on G_j

12: **{Start critical section}**

13: Lock G_i ▷ Mutual exclusion event

14: Add \mathbf{F} to G_i

15: Add \mathbf{M}_i to G_i

16: Unlock G_i

17: Lock G_j ▷ Mutual exclusion event

18: Add \mathbf{F} to G_j

19: Add \mathbf{M}_j to G_j

20: Unlock G_j

21: **{End critical section}**

Algorithm 2 Return contact history

Require:

- 1: G_i ▷ Granule i abstraction
 - 2: G_j ▷ Granule j abstraction
 - 3: $CList_i$ ▷ G_i contact list
 - 4: $i, j \in \mathbb{N} \mid i < j$

 - 5: {**Start critical section**}
 - 6: Lock G_i ▷ Mutual exclusion event
 - 7: **for** each Contact in $CList_i$ **do**
 - 8: **if** Contact contains G_j **then**
 - 9: Set Contact as **active**
 - 10: **return** Contact
 - 11: **end if**
 - 12: **end for**
 - 13: Initialize C_{new} ▷ New contact history
 - 14: Set C_{new} as **active**
 - 15: Append C_{new} to $CList_i$
 - 16: **return** $CList_i$ [end] ▷ Unlock is auto-called
 - 17: {**End critical section**}
-

Algorithm 3 Construction of array $A4$

Require:

- 1: $A3$ ▷ Array $A3$
- 2: n ▷ size of $A3$

Initialize:

- 3: $A4 \leftarrow \text{Array}(\text{size} : n)$
 - 4: Initialize all $A4$ values to $0xffff$ ▷ $0xffff$ is the largest unsigned 32-bit integer on x86 architecture
 - 5: **if** $A3[0].Coord == A3[1].Coord$ **then**
 - 6: $A4[0] \leftarrow 0$
 - 7: **end if**
 - 8: **for in parallel:** $i \leftarrow 0$ to $n - 2$ **do**
 - 9: **if** $!(A3[i-1].Coord == A3[i].Coord) \ \&\&$
 - 10: $(A3[i].Coord == A3[i + 1].Coord)$ **then**
 - 11: $A4[i] \leftarrow i$
 - 12: **end if**
 - 13: **end for**
 - 14: $\text{Sort}(A4)$ ▷ Stable sorting
-

Algorithm 4 Counting Contacts

Require:

- 1: **A3** ▷ Array A3
- 2: **A4** ▷ Array A4
- 3: n ▷ number of active cells in A4

Initialize:

- 4: **A5** \leftarrow **Array**(size : n)
 - 5: Initialize all **A4** values to 0

 - 6: **for in parallel:** $i \leftarrow 0$ to $n - 1$ **do**
 - 7: NContacts \leftarrow 0 ▷ Number of contacts
 - 8: $j \leftarrow 0$
 - 9: **do**
 - 10: $k \leftarrow j + 1$
 - 11: **while** **A3**[j].Coord == **A3**[k].Coord **do**
 - 12: E1 \leftarrow **A3**[j].Elem ▷ Element in **A3**[j]
 - 13: E2 \leftarrow **A3**[k].Elem ▷ Element in **A3**[k]
 - 14: **if** E1 and E2 are in contact **then**
 - 15: NContacts \leftarrow NContacts + 1
 - 16: $k++$
 - 17: **end if**
 - 18: **end while**
 - 19: $j++$
 - 20: **while** **A3**[j].Coord == **A3**[$j + 1$].Coord
 - 21: **A5**[i] \leftarrow NContacts
 - 22: **end for**
-

Algorithm 5 Update array $A7$ from $A7p$

Require:

```

1:  $A7$  ▷ Current contact Array  $A7$  ( $t$ )
2:  $A7p$  ▷ Previous contact Array  $A7$  ( $t-\Delta t$ )
3:  $n$  ▷ size of  $A7$ 
4:  $np$  ▷ size of  $A7p$ 

5: for in parallel:  $i \leftarrow 0$  to  $n - 1$  do
6:   Contact  $\leftarrow A7[i]$ 
7:   Old_Coord  $\leftarrow$  Cell coordinates where Contact occurs in the previous step
8:   if Old_Coord == null then
9:     Initialize  $A7[i]$  ▷ No contact occurred
10:    return
11:  end if
12:  pos  $\leftarrow$  BinarySearch( $A7p$ , Old_Coord)
▷ Backward linear search

13:  l  $\leftarrow$  pos
14:  do
15:    if  $A7[i]$  and  $A7p[l]$  are the same contact then
16:      Update  $A7[i]$  with  $A7p[l]$ 
17:      return
18:    end if
19:    l--
20:    if lft < 0 then break end if
21:  while  $A7p[pos].Coord == A7p[l].Coord$ 
▷ Forward linear search

22:  r  $\leftarrow$  pos+1
23:  do
24:    if  $A7[i]$  and  $A7p[r]$  are the same contact then
25:      Update  $A7[i]$  with  $A7p[r]$ 
26:      return
27:    end if
28:    r++
29:    if r >  $np - 1$  then break end if
30:  while  $A7p[pos].Coord == A7p[r].Coord$ 
31: end for

```

Algorithm 6 Assign forces and moments to the elements

Require:

- 1: **A7** ▷ Contact Array A7
 2: **ElemLst** ▷ Elements list
 3: n ▷ size of A7

Initialize:

- 4: **A8** \leftarrow **Array**(size : $2n$) ▷ Array of IDs
 5: **A9** \leftarrow **Array**(size : $2n$) ▷ Array of Forces
 6: **A10** \leftarrow **Array**(size : $2n$) ▷ Array of Moments
 7: Initialize all **A8,A9,A10** values to $0xffff$

8: **for in parallel:** $i \leftarrow 0$ to $n - 1$ **do**

- 9: Compute force and moments generated in **A7**[i]
 10: **A8**[$2i$] \leftarrow **A7**[i].*ID_Elem1*
 11: **A9**[$2i$] \leftarrow **A7**[i].*F1* ▷ Force in El.1
 12: **A10**[$2i$] \leftarrow **A7**[i].*M1* ▷ Moment in El.1
 13: **if** **A7**[i].*ID_Elem2* is a granule **then**
 14: **A8**[$2i + 1$] \leftarrow **A7**[i].*ID_Elem2*
 15: **A9**[$2i + 1$] \leftarrow **A7**[i].*F2* ▷ Force in El.2
 16: **A10**[$2i + 1$] \leftarrow **A7**[i].*M2* ▷ Moment in El.2
 17: **end if**
 18: **end for**

- 19: **SortByKey**(**A8**,{**A9,A10**}) ▷ Sort an associative array {**A9,A10**},
according to the key **A8**
 20: **ReduceByKey**(**A8**,{**A9,A10**}) ▷ Aggregate the values of **A9** and
A10 according to the reduction
function applied on **A8**

21: $fpos \leftarrow$ first position in **A9** containing $0xffff$ 22: **for in parallel:** $i \leftarrow 0$ to $fpos - 1$ **do**

- 23: **ElemLst**[**A8**[i]].*Force* \leftarrow **A9**[i]
 24: **ElemLst**[**A8**[i]].*Moment* \leftarrow **A10**[i]

25: **end for**▷ Abbreviation: El., Element

Please cite this article as:

J.M. Tiscar, A. Escrig, G. Mallol, J. Boix and F.A. Gilabert

"DEM-based modelling framework for spray-dried powders in ceramic tiles industry. Part II: Solver implementation".
Powder Technology (2020), DOI: 10.1016/j.powtec.2020.08.095

Received 4 May 2020, Revised 15 August 2020, Accepted 29 August 2020, Available online 6 September 2020.

Research highlights

- ▶ A novel GPU and CPU-based DEM algorithm is developed.
- ▶ Any general-purpose contact model can be used without restrictions in the contact searching.
- ▶ The developed algorithms are fairly compared with LIGGGHTS.
- ▶ Developed CPU-based DEM algorithm outperforms LIGGGHTS in demanding filling scenarios.
- ▶ GPU-based DEM algorithm executed on a single GPU does not enhance the CPU-based algorithm.

Please cite this article as:

J.M. Tiscar, A. Escrig, G. Mallol, J. Boix and F.A. Gilabert

"DEM-based modelling framework for spray-dried powders in ceramic tiles industry. Part II: Solver implementation".
Powder Technology (2020), DOI: 10.1016/j.powtec.2020.08.095

Received 4 May 2020, Revised 15 August 2020, Accepted 29 August 2020, Available online 6 September 2020.

Credit Author Statement

J. M. Tiscar: Conceptualization, Methodology, Software, Investigation, Writing – Original Draft;

A. Escrig: Software, Validation.

G. Mallol: Funding acquisition, Resources.

J. Boix: Project administration, Supervision, Funding acquisition.

F. A. Gilabert: Conceptualization, Software, Formal analysis, Supervision, Funding acquisition, Writing
– Review & Editing