Design of Comminution in Ceramic Plants Using a Simulation-Based Optimization Approach

Simulación para la optimización del diseño de instalaciones de molienda para la industria cerámica

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ABSTRACT
The design process of a structural ceramic comminution plant typically consists of an “expert-designer” making decisions using intuitive criteria to select commercial equipment. This paper proposes a simulation optimisation approach to help decision-making. The complexity of the problem lies in selecting the model and number of equipment for each stage with the lowest economic cost while simultaneously satisfying a previously fixed production and granulometry. The proposed approach is based on a genetic algorithm to generate solutions and facilitate the optimisation process, coupled with discrete simulation to evaluate the performance of the comminution process according to its service level. Scenario analyses of the different levels of client requirements in the ceramic industry are performed to evaluate the algorithm.

Keywords: comminution, equipment selection, genetic algorithm, simulation

Introduction
Comminution is commonly defined as the reduction in the average particle size of solid materials. It is usually performed via crushing, grinding, cutting, vibrating, or other processes (Martins, 2016). These processes are commonly used in the mining, pharmaceutical, food, chemical, recycling, and ceramic industries among others.

The structural ceramic industry is dedicated to the procurement of bricks, tiles, and refractories (Cely-Illera, 2016). Majority of companies operating in this sector obtain their raw materials from quarries close to their installations, regardless of whether these quarries belong to them or to third parties. Untreated clay obtained from quarries is transported by truck to the company site, where it is unloaded and stored for later use (Regional Activity Centre for Cleaner Production, 2006).

During the grinding process, untreated clay acquired directly from the quarry is milled, to obtain raw material with the necessary grain-size distribution and texture for subsequent shaping. Two methods can be used to achieve this: dry method and semi-wet method. This study focuses on the dry method; hard clays are best prepared in installations using the dry method. This type of system ensures that a significant proportion of fine particles is obtained which can then be moistened more easily and quickly, resulting in a highly homogenous mass with greater plasticity. As a result, a better finish and a stronger product are obtained.

In the structural ceramic industry, crushers, box feeders, hammer mills, and conveyor belts are common machines used in the comminution process. Although it seems straightforward at first, the sheer number of combinations of all the parameters to consider makes it extremely likely that erroneous estimates will be made or best possibilities will not be explored. There is a need to develop valuable tools for the aid of decision-making in real-world problems...
that are usually solved only by experience (Pradenas-Rojas and Passicot-Guzmán, 2017). The aim of this study is to optimise the selection of the necessary equipment in the comminution of structural ceramics, considering the desired level of production with the lowest possible investment cost.

It is possible to find decision making process in the field of maintenance management applied to grinding processes similar to those presented in this paper (Barberá et al, 2014), as well as in the equipment selection process (Musingwini, 2016). However, in the mining industry, much of this type of process used to be done experimentally despite the costs derived from the decisions taken (Burt and Caccetta, 2018), and moreover, in the structural ceramic industry, it is difficult to find studies focused on the selection of equipment, perhaps because the product has a lower added value.

To optimise a process, it is necessary to be able to simulate and evaluate the behaviour of the industrial plant to ensure that there are no bottlenecks or unnecessary over-sizing. These simulations are common in other fields (Lin and Chen, 2015) and, although commercial programs exist for the crushing process, they are usually focused on the mining industry (such as JKSimMetTM, USIM PACTM, and ModSimTM) and are steady-state simulators. Even though they are adequate in several circumstances, they are unable to simulate transient-states and may lead to erroneous estimates (Asbjörnsson, Hulthen and Evertsson, 2013).

The discrete event simulator has been proved to measure the efficiency of in-plant logistics (Seebacher, Winkler and Oberegger, 2015). Recently, a modular system, developed using MATLAB / Simulink, to simulate the comminution circuits applied to the mining sector has been reported (Légaré, Bouchard and Poulin, 2016). (Negahban and Smith, 2014) is an excellent review of discrete event simulation publications with a particular focus on applications in manufacturing.

It will be evident from later parts of the paper that it is impossible to evaluate all feasible solutions in a short period of time. Therefore, it will be necessary to look for optimisation algorithms that allow finding an optimal solution in a reasonable time period. Guerrero et al (2018) use a multi-objective model based on mixed integer programming combining optimization and simulation techniques. We have chosen a genetic algorithm (GA) approach in this work. GAs are based on the mechanisms of natural evolution which were originally proposed by J. Holland. GA is a search strategy that employs random choices to guide a highly exploitative search, striking a balance between exploration of the feasible domain and exploitation of good solutions. An example of the combination of GA and simulation applied for facility layout problem can be seen in (Wang et al, 2008) where the objective function is the material handling cost.

Note that a previous study (Farzanegan and Mirzaei, 2015) applied GA to optimisation problems of comminution processes and is closely to the problem that affects the subject of this work. Another study (Derpich, Munoz and Espinoza, 2019) applied it in a crushing plant using commercial machines from the Sandvik Company.

This study improves upon existing method in the literature by optimizing the entire design of a comminution process rather than only the parameters that control a previously defined process. This design includes the selection of the equipment at each stage as well as the values of its main parameters to facilitate optimal operation. Therefore, we have programmed a genetic algorithm that designs the process and a simulator that evaluates the design proposed by the algorithm.

**Problem description**

**Process description**

Figure 1 shows the 5 stages of a basic dry grinding process. This type of process is used in the structural ceramic industry when the clay moisture is less than 10-12%. The comminution in a dry grinding process is typically performed in two stages using a cruscher and a hammer mill consecutively to achieve the optimum granulometry needed in the extruder. The extruder needs a continuous flow of material, while cruscher receives a batch flow. The raw material extracted from the quarry is dosed into the cruscher via a dumper truck or wheel loader every time the hopper reaches a previously fixed level.

There are feeders with hoppers between these machines in order to avoid bottlenecks and homogenised the material flow.

![Figure 1. Comminution basic stages of a Dry Grinding Process. Source: Authors](image)

Each stage has a number of identical equipment (n_k), and each equipment consists of one machine (M_k) and one hopper (T_k). A particular machine model can be fitted with different types of hoppers. The storage capacity increases with height, but the total height (machine plus hopper height) is limited by the inside height of the factory. \( P_{S_k} \) is the stage production (t/h) and \( P_k \) (t/h) is the equipment production in stage k; thus \( P_{S_k} = n_k * P_k \).

The conveyor belts move material between the stages. Their speed and inclination are design parameters and depend on the model chosen. The length is determined by the height of the equipment that receives material, and the width is calculated to ensure the capacity is sufficient to carry the maximum output of machine collecting material. The value of material waste during transport between stages is typically 5% or less of the material moved at each stage.

The extruder or stage k=0 is the process client. It kneads the clay with water to obtain the desired shape by extrusion and vacuum. This equipment needs a continuous and
uninterrupted material flow with a fixed granulometry. The client determines both parameters, $P_{S_{k=0}} = P_{S_0}$ (t/h) and $k=0 \Rightarrow 0$ (mm).

Primary feeders or PFs ($M_1$) dose the exact production required in the extruder. Each feeder draws a variable production $P_{k=1}$ (t/h) from its hopper. The total stage production must be equal to $P_{S_0}$, but the production of each feeder may vary within a range according to material availability.

Hammer mills or HMs ($M_2$) break the material to decrease its granulometry (see Figure 2). The diameters of screen holes are fixed to match the granulometry needed in the extruder ($d_2 = d_0$). The HM model production is fixed, and the overall production sent to PFs is the result of multiplying the number of active HMs (the ones with material in their hoppers) by their nominal productions. They stop once PF hoppers are full and run again when some of their levels are below a reserve level, usually, 40% of their capacity and all available HMs send material to the corresponding PF hopper.

Stage 5 models the way in which trucks or wheel loaders directly transport the raw material from the quarry. Batch process size, number and tempo depend on hopper capacity $T_4$. In this work, we have decided that the simulator would use wheel loader when the capacity of the hopper was small and dumper trucks in the rest of the cases. The average charge cycle time has been considered 5 and 20 minutes respectively.

Process parameter

Principal parameters that control the process are demanded by the client: extruder continuous production, $P_{S_0}$[t/h], and extruder granulometry, $d_1$[mm]. Raw materials granulometry at the quarry, $d_2$[mm], and available height inside the factory, $H$[m], are other parameters affecting the performance of the plant.

Bulk density is a significant factor because clay is a granular material, and density depends on particle size. Equation (1) defines a linear relationship between (diameter below which 80% of material passes) and density based on a company experimental dataset. Therefore, density grows as grain size decreases, and the material becomes more compact. This indicates that flow demanded by the extruder [m$^3$/h] will be less than the flow of clay at the entrance.

$$V = \frac{H \cdot \sum_{i=0}^{d_2} \sum_{j=0}^{d_1} [x_{ij}^{d_1} \cdot y_{ij}^{d_1}] - \sum_{i=0}^{d_2} \sum_{j=0}^{d_1} [x_{ij}^{d_1} \cdot y_{ij}^{d_1}]}{T_{4}}$$

(1)

Considering these parameters and available commercial models, the designer defines a set of machines and hoppers for each stage and chooses a specific one from these sets. Let $M_k = \{1, \ldots, q_k\}$ be the set of feasible machines in the stage $k (k = 1, \ldots, 4)$ with $q_k$ as the maximum number of selectable machines. $T_{ik}$ is the set of feasible hoppers for each machine in the stage $k$, with $i_k M_k$. Therefore, the problem is to select the machine and the hopper model in each stage $k$ as well as their respective numbers. The decision variables are as follows: $x_{ij}^{d_1}$, machine model that equals 1 if the model that occupies the position $i$ in $[M_k]$ is selected; $y_{ij}^{d_1}$ hopper model that equals 1 if the model that occupies the position $j$ in

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**Figure 2.** Hammer mills.

**Source:** Authors

Secondary feeders or SFs ($M_3$) feed HMs in a similar manner as PFs do, although they do not necessarily feed the exact amount of material that HMs produce. Once all the HM hoppers are full, the feeders stop and resume when a hopper reaches the reserve level. Material flow must be equal to or higher than the amount needed by the HMs in order to receive sufficient material in a timely manner every time they are set in motion. This parameter called “production multiplier” should be set up in the design process.

Crushers ($M_4$) decrease the grain size of raw material (see Figure 3) stored in their hoppers $T_4$. The diameter of the raw material, $d_3$, is an initial condition of the problem; otherwise, the diameter from the material that goes out of the crusher, $d_4$, vary between a set of values. This is important because the size selected influences the work done by the HM.

Stage 5 models the way in which trucks or wheel loaders directly transport the raw material from the quarry. Batch

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**Figure 3.** Crushers.

**Source:** Authors
\{T_{i,k}\} \text{ is selected; } n_k, \text{ number of equipment (machines plus hopper) in each stage.}

As the comminution is done in two stages, it is necessary to define the output diameter at the crusher, \( k = 4 \). As the possibilities are many, a set \( \{A\} \) of \( n_{\text{max}} \) dimensions is defined with the most common values. The second variable is the production multiplier for the secondary feeder, which are limited to a set \( \{A\} \) of \( n_{\text{max}} \) dimensions with values between 1 and 2. The production value given by these feeders is theoretical necessary production at the extruder stage multiplied by this factor \( a \).

**Optimization approach**

**Genetic Algorithm**

Design experts, depending on their subjective experiences, typically judge a huge combination of feasible solutions to select an optimal solution. But not all solutions are really feasible. Thus, some solutions tend to be over-dimensioned if the designer is focused on reliability, while some solutions lead to a lack of production the designer is focused on cost. Hence, each solution needs to be simulated to evaluate its performance, but this is time-intensive and not feasible.

A GA has been developed to solve this problem. The goal is to find an optimal solution that minimizes installation cost while ensuring a feasible solution (extruder continuous production and granulometry; maximum installation height). Each solution is codified as an integer 14-dimensional vector, and gene values indicate the positions of selected elements in the set. Thus, the chromosome structure is \( \{n_1, i_1, j_1, a, n_2, i_2, j_2, a, n_3, i_3, j_3, a, n_4, i_4, j_4, b\} \), where \( n_k \) is the number of equipment (machine and hopper) corresponding to block \( k \); \( i_k \) is the position of machine model in the set \( \{M_i\} \); \( j_k \) is the position of hopper model in the set \( \{T_{i,k}\} \); \( a \) is the position of the production multiplier parameter in \( \{A\} \); and, \( b \) is the position of the selected diameter \( k = 4 \) in \( \{B\} \). All values rank between 1 and 5.

The GA starts with a randomly generated population, Basic-Population (BP), of feasible \( N_{\text{pop}} \)-solutions whose cost or fitness is evaluated. Then, a new population will be formed by selecting individuals from this BP to create offspring of a subsequent generation. Every basic-solution has a predetermined probability \( p_c \) to belong to a parent-population. Subsequently, a best-worst crossover operator is applied for establishing parent-chromosomes pairs and generating two offspring from each couple. Each offspring gene is randomly selected from one of the parents. After the crossover, the mutation operation is carried out. A chromosome of the offspring population is selected for the mutation operation with probability \( p_m \), and the values of 3 genes change randomly. Each of these solutions is evaluated in a computer model specially designed to simulate its behaviour; a solution is rejected if it is infeasible.

In assessing the fitness of new feasible offspring and muted-solutions, the algorithm selects the best solutions (parents, offspring and muted) to survive and updates the BP. Additionally, a heuristic technique is applied to improve the quality of BP solutions. The method consists of randomly choosing a block or stage \( (k = 1 \ldots 4) \) and changing all parameters of the selected block. Finally, the last iteration step is to choose the best solution found, and finish the improvement method for this iteration. The best feasible solution is selected when the maximum number of iterations is reached.

**Model simulation**

Apparently, the problem and the solution proposed by the algorithm seem simple, since also there are no components of variability in the system (it is assumed that the clay to the entry has the same particle size, times are fixed, etc.). However, when the behaviour of the different equipment is simulated and the evolution of hopper levels overt time is evaluated, this behaviour becomes dynamic and seemingly chaotic.

The operation of each stage is conditioned by both the anterior and subsequent stages and the flows take time to stabilize. It is therefore difficult to predict where and when bottlenecks can be found, and the existence or not of oversized elements. Figure 4 illustrate the evolution of the capacity (m³) of a hopper of feeder. Initially, the hopper is full and begins to empty in a linear manner but soon the behaviour becomes chaotic when the material demand and filling cycle have different and chaotic periods. Some examples of this type of behaviour can be found in (Légaré, Bouchard and Poulin, 2016) and (Li et al., 2018).

![Figure 4. Capacity (m³) vs time (h) in a feeder hopper.](source: Authors)

Therefore, a simulation model has been designed to evaluate the operation of the installation over a sufficiently long period of time to ensure that the model reaches all states. So, we can check the feasibility or not of each of the solutions proposed by the GA. To do this, we evaluate the flow of material that reaches the extruder every hour during the testing time, \( PR_T \) (t/h) \( T = (1\ldots\text{total simulation periods}) \), and compare it to the design parameter, \( PS_0 \) (t/h). Thus, the Service Level \( (SL_T) \) is defined as the relationship between \( PR_T \) and \( PS_0 \).

The simulation model has been programmed in Matlab and, in addition, other parametric model was built using WitnessPwF© to validate the results. The results of the two approaches are very similar and the differences are not
After several rounds of testing, simulation time will be at least 50 hours for all states to appear; the warm-up period necessary is 5 hours. Thus, the computing time to simulate each GA proposal is 40 seconds.

### Research results and discussion

#### Computational results

The algorithm was implemented in industry to prove its performance. Usually, the ceramic industry production values range between 50 and 150 t/h, so machines are sized to fit these requirements. However, there are cases where much larger productions are needed and where success business stories to compare are much more limited. Thus, 8 levels of extruder production (25-50-100-150-200-250-300-400 t/h) and 2 levels of particle size reduction (125, 5/1 and 81, 2/10) have been identified, and the number of experiments is 16.

Taking these requirements into account, available commercial models are selected. The models and parameters used in this study are based on real-world equipment of a company located in Zaragoza Spain, dedicated to the design and manufacturing of machinery for treatment and preparation of clay in the ceramic industry. Table 1 shows various parameters such as the range of flow rate, capacity and cost of feasible equipment at each stage. To facilitate the comparison of results, the set of machines and hoppers for each stage is the same for all experiments. Note that the selectable models at feeder stages are identical. On the other hand, crusher machines have higher flow rates than hammer mill models because of the presence of waste material between stages, and also because material is compacted as the process progresses.

<table>
<thead>
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<th>Table 1. Data to design ceramic industry</th>
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<td><strong>Stage 2: Hammer Mills</strong></td>
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<td>No. models: 25 (5 HM’s and 5 Hoppers)</td>
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<td>Q (m³/h): 22 63</td>
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<td>Capacity [m³]: 1,4 4,67</td>
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<td>Cost [€]: 76 105 15 0674</td>
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<td><strong>Stage 4: Crusher</strong></td>
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<td>No. models: 25 (5 Crushers and 5 Hoppers)</td>
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<td>Q (m³/h): 25 114</td>
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<td><strong>Stages 1 and 3: Feeder</strong></td>
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<td>No. models: 25 (5 Feeders and 5 Hoppers)</td>
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<td>Q (m³/h): 10/40 90/12</td>
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<td>Capacity [m³]: 1,34 67,08</td>
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<td>Cost [€]: 32 000 61 139</td>
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<td><strong>Belt conveyor</strong></td>
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<td>Cost = Fixed term proportional to number of conveyors between stages + variable term depending on the length and width</td>
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</table>

Otherwise, caudal output at crusher, \( Q_{CRUSHER} \), is subjected on \( k = 4 \), and increase as with the diameter (the \( Q_{k=4} \) interval in Table 1 is for the minimum diameter, \( k_{min} = 24 \) mm). The hammer mills caudal, \( Q_{k=2} \), is not directly influenced by particle size and production, but hammer velocity, inlet position, breaker gap, infeed granulometry, screen size and others have minimum influences on this parameter. In order to simplify the model, a constant and independent production has been considered.

The numerical experiments have been performed on a Windows 7 PC with an Intel® Core™ i7-6800K CPU®@3.4GHz and 16GB RAM. The GA and code for the simulation model have been written in MATLAB®.

To simulate each solution, simulation time was set to 50 h with a 5 h warm-up period; computational time was around 38 s per solution. The average computing time to make the iterations prescribed was 6.7 h, and the algorithm evaluated approximately 630 solutions. Each test instance was being solved 8 times and the best results are listed in Table 2 and Table 3.

Table 2 shows best results configuration and cost of best results. The first three columns define the numeration and settings of the experiment. Column 4 refers to the cost [M€] of the best solution found among the eight solutions obtained. Columns 5 to 6 refer to the Primary Feeder stage \( (k = 1) \), listing the number of machines and unitary cost equipment [M€]. The rest of the columns contain similar information for the Hammer Mills \( (k = 2) \), Secondary Feeder \( (k = 3) \), and Crusher \( (k = 4) \) stages.
Table 2. Best results of the instances: cost

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<td>4</td>
<td>145</td>
<td>3</td>
<td>45</td>
<td>3</td>
<td>73.3</td>
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</tbody>
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Source: Authors

Table 3 displays the number of machines, flow rate and capacity of best solutions to all stages. The results suggest that installation cost is strongly related to production, and the cost of all stages rise as $P_{S0}$ increases. When scenarios with the same productions are compared, it is evident that the value of the particle size reduction is not relevant. Hence, the algorithm proposes identical configurations (number and type of machine and hopper) for each level of extruder production, even when the particle size reduction changes, except in the case for crushers of $P_{S0} = 150t/h$. The conveyors cause small differences (note that installation cost decreases, as expected, but only 0.5% of the maximum); as clay is more compact, conveyors are narrower and cheaper.

Analysing each stage configuration, the algorithm proposes high production HMs and medium–low production crushers. On the other hand, hoppers of all stages and experiments are as small as possible, to ensure equipment height is as short as possible, which allow for shorter and cheaper conveyors to be used. Finally, note that size reduction in the first crushing stage, $IN\cdot k = 4$ is the least possible. Moreover, $k = 4$ takes medium to high values, independently of the initial and final granulometry. This way, the crusher processes as much material as possible, although the crushing is not so severe.

Figure 6 shows, for each production level, the individual cost [\text{ME}] of every stage including conveyors. As expected, the cost of all blocks increases as production rises.

Figure 7 displays the cost relative to global cost for each problem [%], and particular emphasis is given to the relative cost of hammer mills. On the other hand, conveyors account for 20-25% of installation costs, although this cost is not considered during product design as they are considered as an auxiliary system.

Figure 8 shows cost relative of $P_{S0}$. Relative cost is very high for small values of $P_{S0}$ because of the equipment being oversized; at higher productions, the relative cost does not change too much, and these small differences are due to discretisation of equipment parameters (capacity, flow and cost).
The solutions provided by the GA are similar to those adopted in ceramic industries, but some interesting alternatives appear in the design of facilities.

Normally, hoppers are placed as high as possible except at the hammer mills stage. This decision is usually taken because of doubts that the line is not balanced and properly dimensioned. This results in conveyor belts that are much longer and need a larger area for the comminution zone, increasing the cost of hoppers and, especially, belts, which can represent 40% of investment installation. In addition, this over-dimension also causes an increase in energy consumption.

Finally, it is noteworthy that this work has been approximated in the most realistic way possible, using commercial equipment with sizes and prices related to the relevant industry. For large production cases, capacities of hammer mills are insufficient and a higher capacity model needs to be developed.

**Conclusions**

In this paper, we have parameterised and characterised a comminution process of ceramics where the dry grinding process is done using two machines: crusher and hammer mill. We propose a simulation-optimisation-procedure-based GA to obtain an economical solution to the problem of equipment selection. In this study, we have considered the cost of all the installation equipment and the ratio between the actual and demanded production at the extruder during the considered period of time.

To assess the feasibility of the solution, it has been necessary to develop a simulation model that, via time discretisation, calculates production and material granulometry obtained, and the service level. Because of the high computation times needed to evaluate production, it has been necessary to consider different strategies in the GA, including local improvement, to select an optimal solution in a shorter time. Finally, the proposed method has been tested with a variety of real-world problems faced in the ceramic industry, evaluating how the cost of the plant and the type of equipment is distributed in each block or stage. Such calculations can be done for a wide range of combinations of machines and hoppers, with respect to both number and sizes.

With regard to the results obtained, it should be noted that the installation cost is strongly related to production, but not to the particle size reduction. It also highlights that the need for hoppers of all stages and experiments to be as small as possible, to ensure that equipment height is as short as possible, and, therefore, allowing for the use of shorter and cheaper conveyors.

The capacity of the system presented in this article to design comminution plants has been proven. Finding a best possible solution that fits with the needs of the client presents possibilities of new ways of working that would allow companies to not depend on the criteria of the expert when designing new plants for the structural ceramic industry.

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**References**


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