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A Methodology for Automated Pellet size Distribution in a Pellet Mill

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Abstract
In this work the feasibility of pellet size distribution using images captured from the operator's sight glass of the moving pellet bed using a standard digital camera is investigated. The pellet size distribution is determined using a bespoke circle detection program which is able to fit circles to pellet edges, neural networks are used to match predicted distributions to actual distributions and discrete element modelling is used to create a large quantity of rendered images with known distributions for network training. The results show that the circle detection algorithm is able to find a high percentage of pellets in an image and find their sizes. Neural networks are then able to use the predicted pellet size distributions to give a good prediction of the actual distributions and are able to account for segregation effects in the pellet beds. This demonstrates that an online pellet sizing scheme is feasible in nickel pellet production.

1. Introduction

Nickel pellets are produced via the carbonyl process. Small seed pellets are added to a reactor and grown to the required size before being removed. The behaviour of the reactor is strongly dependent on the size distribution of the pellets within it. The behaviour of the reactor can be controlled by adding pellets or purging pellets. Currently these requirements are decided on by an operator who looks into the pellet reactor through a viewing glass and then decides whether to add or purge pellets based on experience. Clearly this is a less than ideal situation as the operator is prone to factors such as illness or retirement. It is therefore desirable to have a simple non-intrusive method to find the pellet size distribution of the bed at any time. This can eventually be related to the seeding/ purging requirements. An automated seeding/ purging system will lead to better process control and greater efficiency. In this work the feasibility of using photographic images captured from the operators sight glass to estimate the pellet size distribution in a pellet bed (inside the reactor) is investigated. The recognition of features or shapes in images is an important area of research and crosses over many scientific fields [1] [2].

Nickel pellet beds can be several pellets thick. The captured image will only show the top of the bed. The pellet distribution of the image will not match the actual distribution due to smaller pellets being hidden and segregating to the bottom of the bed (see Figure 1). This is demonstrated from experiments using static piles of pellets with known distributions. Nickel pellets are almost perfectly spherical in shape. In a 2D photograph they appear circular. Therefore an image analysis application has been developed to fit circles to the pellets that can be seen in the image. Due to segregation of pellets the size distribution in the image will not represent the true size distribution of the pellet bed [3]. The distribution will be skewed towards larger pellet sizes as the smaller ones can move through gaps in the bed and be hidden by the larger ones. Neural networks have been used to fit the pellet size distribution detected by the circle detection algorithm from an image to the actual distribution within the bed.

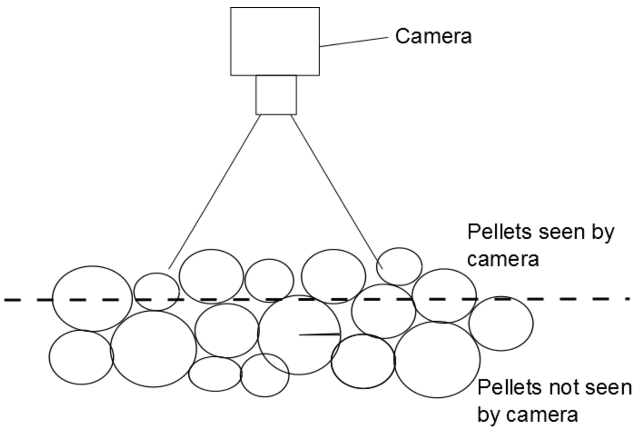

Figure 1 Only top layer of pellet bed seen by camera

Neural networks are a computer modelling technique based on the neural pathway connections found in the brain. The network can ‘learn’ patterns and trends between inputs and outputs within a data set and then be used to predict outputs from data sets where the outputs are unknown [4]. A large quantity of data is required to ‘train’ the neural. Generating such large data sets from physical experiments is prohibitive. Neural networks require a broad range of input and output parameters to be able to give a good general prediction. Pellets require mixing and sieving to generate a sample of the pellet bed and to find the actual size distribution which is time consuming. We have found that a maximum of three samples could be made a day, whereas the neural network would require ~10000 samples to give reasonable predictions. Therefore a method of generating virtual samples using discrete element method DEM was investigated [5].

DEM with known pellet size distributions has been used to investigate whether given enough experimental data if neural networks are an appropriate tool to find the true pellet size distribution compared with the distribution given by the image software. The results of the DEM model can be used to render almost photo-realistic images of pellet locations. The circle finding algorithms can be used on the virtual images and the distributions it predicts can be compared with the known distributions.

Using the DEM simulations 10,000 data sets were generated with different pellet distributions. From these DEM simulations images of the pellets were rendered and the circle detecting application was applied to them. The distributions predicted by the circle detecting application were used as the inputs of the networks and the actual distributions as the outputs during training.

2. Image analysis

Several algorithms to detect circles in images have been investigated for this work, such as the Circular Hough transform [6], but found to be not suitable for this particular application. As such a bespoke image analysis application, written in C++ and QT4, has been developed to fit circles to circular edges within images. The application is able to fit to partial boundaries and can detect circles where part of the edge is hidden. Figure 2 shows an image of a pile of coins with some hidden edges. The red circles on the image show where the application has found a circle [6]edge.

Figure 2 Circle detection algorithm performed on pile of coins with some hidden edges

The basic outline of how the application works is as follows:

1. The image is converted to greyscale
2. A Sobel filter is applied to the image. The Sobel filter approximates the gradient of an image. At pellet edges the gradient is high.
3. Using the gradient information areas of gradient which are below a threshold are discarded, leaving only the pellet edges.
4. Uniformly distributed circle centres are generated across the image.
5. From these centres circles grow by incrementally is radius approximately one pixel at a time. The edges of the circles are then checked to see if any portion of them is at the same location as a pellet edge. If they are close the circle centre can move to try to get a better match.
6. The location of matching circle centres and their radius is stored and the application moves onto the next circle growth routine.
7. If there are many matching circles of similar size these are averaged so each match is only counted once.

The application returns a circle size distribution from the image. The application has been applied to real images of nickel pellets. In general it finds the edges of most of the pellets and fits a circle with the correct radius. This is shown in Figure 3

Figure 3 Circle detection application on actual pellet images

3. Discrete element modeling and rendering

Discrete element modelling (DEM) is an explicit numerical technique where the physical interactions between particles are modelled over a small time step first implemented by Cundall and Strack [7]. In general DEM deals with spherical particles and applies various frictions between them to deal with surface roughness and irregular shapes. Since nickel pellets are relatively spherical in shape they make an ideal case study for DEM work. DEM has previously been shown to give good predictions of nickel pellet behaviour [8]. In a DEM simulation particle boundaries are allowed to overlap slightly and the forces generated are calculated based on the overlap and contact models. Accelerations and velocities can then be calculated for the next time step. In this work a Hertz-Mindlin model is used for the normal and shear forces [9] [10]. A leap frog integration scheme is used so pellet positions and accelerations are calculated at time step t_n and velocities at $t_{n+1/2}$, where n is an integer that indicates the current iteration.

In this work simulations of static piles of pellets were generated using the open source DEM software YADE [11]. Spheres were generated randomly in a space above a container before the simulation started. The simulation was then started and the pellets allowed to fall into the container under gravity and settle. The distribution of pellets sizes was Gaussian and divided into six bins spanning a range of size values from 1mm to 14mm. The pellet distributions were generated using a Latin hypercube method which ensures a good spread of data.

Using open source rendering software (POVRAY) [12] almost photorealistic virtual images can be generated as shown in Figure 4.

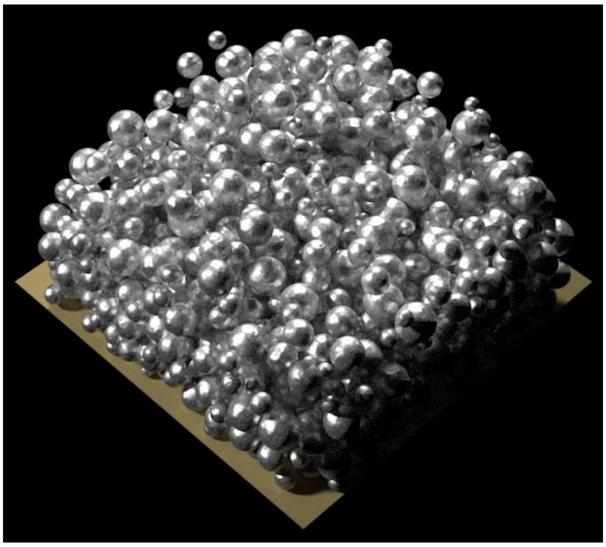

Figure 4 Image generated from a DEM simulation using POVRAY rendering software

The virtual camera can be positioned to view any area of the scene. In order to generate a training set of data for neural network analysis 10,000 images with different particle distributions were generated from DEM simulations by having the camera looking vertically down on the virtual pile of pellets. A typical image to be analyzed is shown in Figure 5. Figure 4 shows a typical depth of pellets (note the walls confining the pellets are set to be invisible in the rendering software).

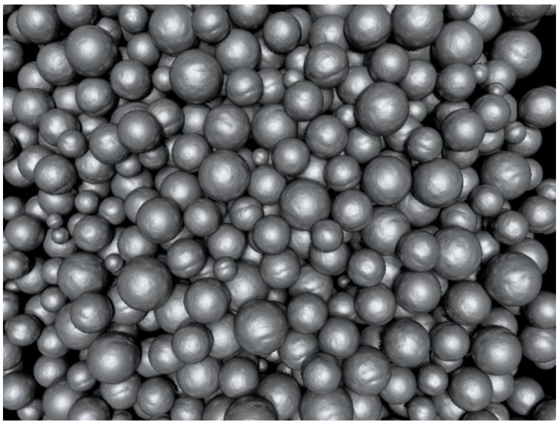

Figure 5 Virtual image looking down on a static pile of virtual pellets

Figure 6 shows the same image as Figure 5 after the circle detection algorithm has been applied to it. In general it does a good job of locating the pellets and fitting circles of the correct radius to them. The detected pellets are circled in red.

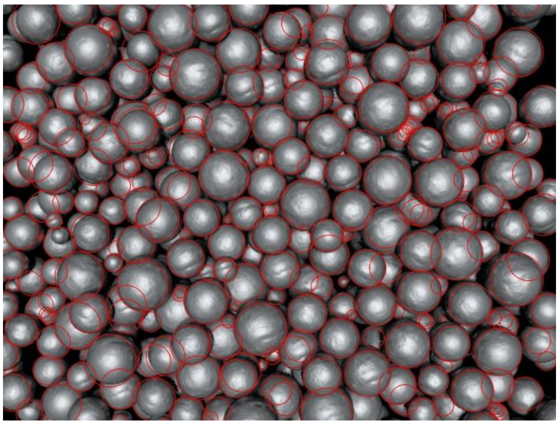

Figure 6 Circle finding algorithm performed on a virtual image (pellets are circled by the application)

While these simulations are simple with further work DEM simulations should be able to show a good representation of actual particle dynamics.

4. Neural network analysis

As mentioned in the introduction, the pellet distribution that can be seen from the top surface is not the same as true distribution due to segregation effects. The segregation will be dependent on the particle size distributions and not predictable. Neural networks use weighted nodes with a bias and are capable of mapping highly non-linear relationships between input and output parameters [4]. By changing the weighting of the nodes and the bias during the training procedure neural networks are able to pick out complicated patterns and trends within a data set.

In this work the neural network analysis was conducted using the MATLAB neural network package [13]. After studying different network architectures the network was set up with a single hidden layer with nine nodes and was fully connected. There were six different network inputs which correspond to the six pellet size bins. The value entered is the ratio of the total number of pellets in each pellet bin (i.e. sum of all bins = 1). The size bins (were based on the sieve sizes of the physical experiment) and shown in the table below.

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Bin	**1**	**2**	**3**	**4**	**5**	**6**
Sizes(mm)	1-4	4-6.3	6.3-8	8-10	10-11	11-14

The network has six outputs which correspond to actual number of pellets in each pellet bin. Tansig functions are used as the transfer function of the nodes in both the hidden and output layers. The network architecture is shown in Figure 7.

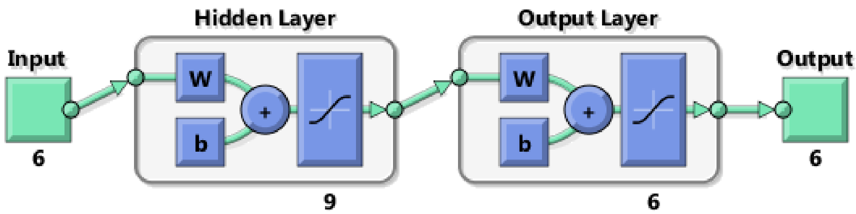

Figure 7 Neural network architecture

For training the input data is divided into randomly three sets, 70% into a training set, 15% into a validation set and 15% into a test set. For more information on these sets the reader is referred to Haykins [4]. The network is trained using a Levenberg-Marquardt back-propagation algorithm [14]. Training is stopped once the mean square error of the validation set begins to increase, indicating over fitting to the training set.

5. Results

Figure 8 shows the R^2 plot of pellet distributions as predicted by the circle detection application vs the actual distributions for all data sets. The R^2 value of 0.080404 show that the predicted values of the pellet distribution are not matching the actual values, as expected due to segregation. Figure 9 shows the R^2 plot of all data sets once the distributions predicted by the circle detection algorithm has been passed through the trained neural network. The R^2 value of 0.9885 shows that the outputs of the distributions from the neural network and the actual distributions are well correlated.

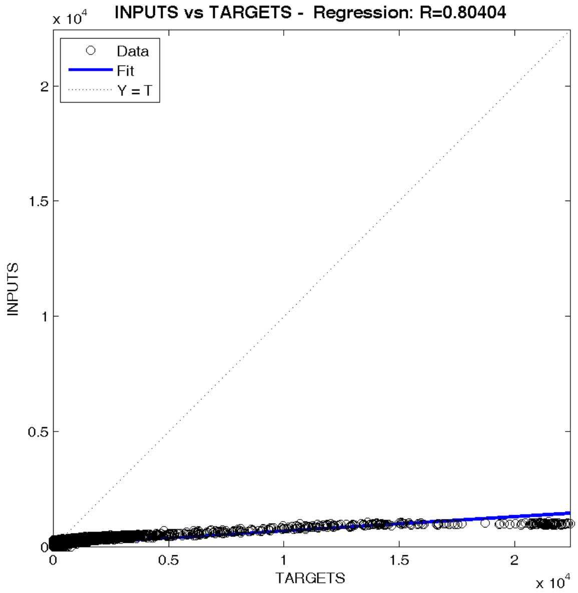

Figure 8 R^2 of pellet distributions predicted by circle detection algorithm vs actual distributions (number of pellets)

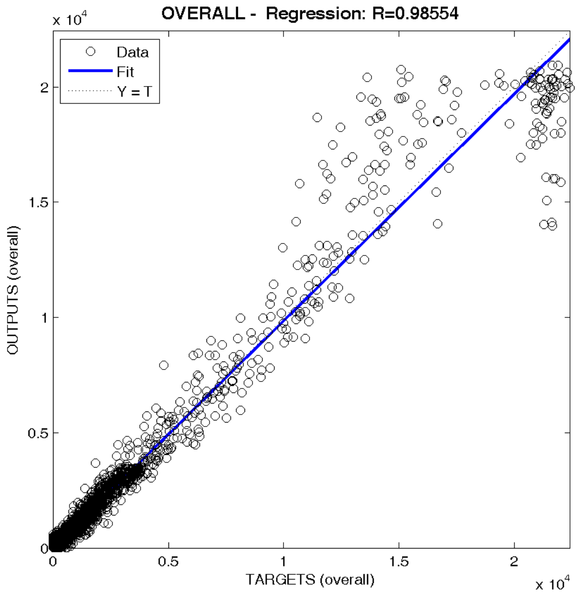

Figure 9 R2 of pellet distributions as predicted by neural networks from circle detection algorithm inputs vs actual distributions (number of pellets)

Figure 10 shows plots of individual samples from the data set showing distribution of pellets in each bin. The blue bars show the number predicted by the circle detection algorithm, the green the actual values and the red the values predicted by the neural networks with the predicted values as the inputs for the network.

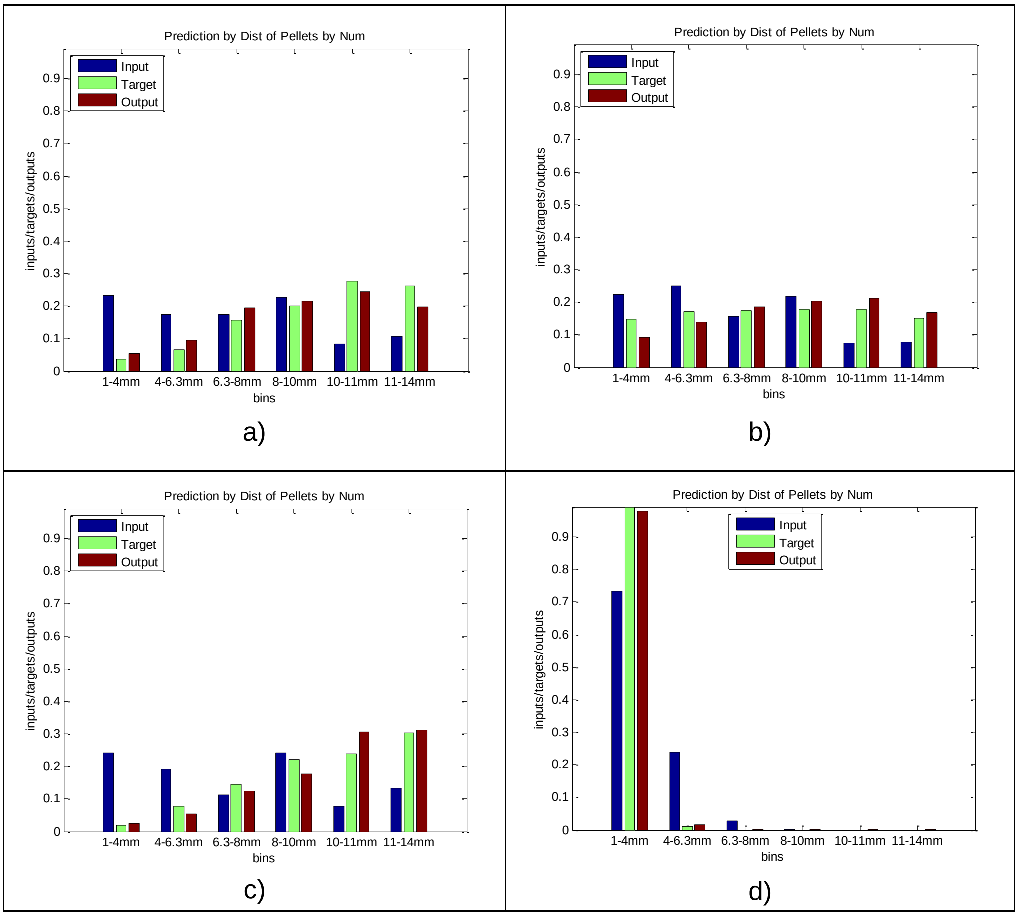

Figure 10 Plots from individual images showing predicted circle detection app, the actual (target) and actual pellet distributions

From the plots in

Figure 10 it can be seen that the results given by the neural networks is significantly closer to the target values than the results given by the circle detection algorithm. For plots a, b and c the ratio of small pellets is higher than the large pellets which is not what would be expected due to segregation effects. This may be because the pellets are dropped in position and after coming to rest there are no further dynamic effects. To truly see the segregation effects more complicated DEM simulations involving dynamic movement of the bed must be performed. What is clear is that the trained neural network is able to give good estimates of the actual pellet distributions based on the distributions found by the circle detection application. There is a relationship between the actual distributions and those found by the circle detection application which the neural network is able to find. Unfortunately neural networks are a 'black box' technique so cannot be used to find the statistical relationship.

6. Conclusions

In this paper an image analysis technique has been demonstrated to find the edges of nickel pellets visible from a static image. The circle detection application developed is able to find most pellets in the image, including partially hidden ones and give a good estimate of their radius. Neural networks can be used as a method to give a good prediction of the actual distributions when compared with those predicted by the circle detection algorithm. The DEM modelling requires further work to accurately describe the dynamics of a pellet bed, but shows good potential and along with rendering techniques the images produced could be used to train neural networks in the future. This work suggests that it would be feasible to have an automated pellet sizing system on the sight glass of a pellet reactor.

Future work

There are several areas of further work which should be

- Dynamic DEM simulations of pellets moving as they would in the reactor so segregation effects can be seen clearly.
- Neural networks with other inputs such as height of the bed (in this simulation the height so of the static piles are approximately the same). The height of the bed could have further impact on the segregation, i.e. a deeper bed will result in greater segregation.

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