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Highlights

Frequency Domain Analysis for Identifying Dominant Segregation Units in a Chain of Material Handling Processes: A Cellular Automaton Framework

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- A novel Frequency Domain Analysis (FDA) approach identifies dominant segregation units in pellets handling chains, based on validated Cellular Automata (CA) models.
- FDA analysis indicates that segregation in smaller silos (2,500 tonnes) is negligible when materials are transferred to larger storage units (90,000 tonnes).
- The FDA method reduces simulation complexity by eliminating the need for full-chain modelling, providing a novel computationally efficient alternative for predicting segregation.

Frequency Domain Analysis for Identifying Dominant Segregation Units in a Chain of Material Handling Processes: A Cellular Automaton Framework

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Abstract

Degradation and material segregation are persistent challenges in bulk solids handling. During storage and transport through silos, domes, ship holds, and hoppers, mechanical stress generates fines and dust, exacerbating segregation and reducing process efficiency. This can cause fines spikes during silo discharge, increasing the risk of fire and dust explosions, raising energy consumption, and elevating maintenance needs. Moreover, variability in fines content in material stream negatively impacts downstream processes such as milling, combustion, and emissions control. To address the challenge of modelling segregation in multi-stage wood pellet handling systems, a Cellular Automaton (CA) model was previously developed to simulate segregation at individual transfer points. However, full-chain simulations remain computationally intensive. This study introduces a novel Frequency Domain Analysis (FDA) method to identify the most influential segregation stages, allowing simplification of the modelling scope. In this framework, each storage unit is conceptualised as having a "forcing function" that introduces its own segregation pattern, and a "damping function" that attenuates upstream effects. Applied to large-scale systems, FDA enables quantitative assessment of how each unit contributes to downstream segregation. The analysis revealed that inflow signals with frequencies below a corner frequency of 0.5 pass through the system and induce segregation, while higher frequencies are increasingly attenuated. This approach supports the development of targeted, efficient handling strategies by isolating critical stages for detailed simulation. The proposed approach enables focused mitigation strategies, directing attention to handling stages with the greatest influence by maximising both process efficiency and operational safety.

Keywords: Cellular Automaton model, Frequency Domain Analysis, Bulk Material Handling

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1. Introduction

Due to rising demand for green energy and different legislation to minimise carbon dioxide emissions, most power generation companies are switching to wood pellets to replace coal [1, 2]. Wood pellets are a sustainable energy source that can be regenerated naturally [3, 4]. However, during handling, wood pellets degrade into fines and dust due to various factors. Particle collisions with other particles, as well as impacts between solid edges and container walls, are common causes of degradation. The presence of fines and dust in clean wood pellets causes considerable handling difficulties [5].

Segregation is one of the primary challenges encountered in bulk material handling, particularly in wood pellets [6, 7]. It can lead to a range of operational and safety issues, including inefficient pneumatic conveying [8], suboptimal milling performance [9], and inefficient combustion in furnaces [10], which in turn results in the release of unburned carbon and associated disposal challenges. Furthermore, segregation increases the risk of fires and dust explosions [11, 12] and contributes to significant health and environmental hazards [13, 14, 15, 16]. The operational cost for cleaning [17], and maintenance also increase due to soot and dust emission. Therefore, predicting segregation, fines and dust spikes in bulk material handling is important for mitigating these operational challenges.

While segregation can be predicted using traditional continuum methods [18, 19], discrete element modelling, and other numerical techniques [20, 21], these approaches often rely on high-performance computing and remain computationally demanding, particularly when applied to large industrial-scale silos handling tens of thousands of tonnes of material. This limitation has led to the development of more macroscopic modelling strategies, such as continuum models and population balance models (PBMs) [22]. However, these methods often lack the spatial resolution and flexibility required to capture localised segregation phenomena effectively [23, 24, 25]. Continuum models tend to smooth out discrete segregation effects, while PBMs require extensive calibration and become increasingly complex when applied to spatially distributed systems [22, 24]. In contrast, the Cellular Automata (CA) approach adopted in this study offers a spatially discrete, rule-based framework [26, 27, 28] that enables efficient modelling of local heterogeneities and segregation propagation across large-scale systems, without the need for intensive computational resources. For example, simulations of silos containing up to 30,000 tonnes of wood pellets using the CA method have yielded highly accurate results within significantly reduced computational time [9].

Common pellet handling chains include several transfer points, each contributing to successive stages of segregation during silo filling. To use control mechanisms to ensure uniformity in the material stream during discharge, relatively accurate segregation analysis must be obtained in a short period of time. However, the time required for an integrated process modelling and simulation is uncertain and likely to be longer, which discourages the use of models to forecast segregation and use common practice. Therefore, it would be ideal to develop a method capable of identifying segregation within the wood pellet handling chain, or pinpointing the key contributors, so that appropriate control measures can be implemented to mitigate upstream segregation effects.

A typical example of a pellet handling system in leading power the UK based power generation

company includes multiple storage units from port to mill. For instance, silos at the port hold up to 30,000 tonnes of material for short-term storage, while silos at the rail load-out have a capacity of around 2,500 tonnes. During handling, materials in a large silo might divided into small batches, and at some point such small batches are collected and stored in a larger silo and domes. Eventually, the wood pellet trains are then transported and gathered to a bigger dome with a capacity of 90,000 tonnes in another location. During the subdivision of larger silos, different segregation patterns may be seen in small batches. However, such segregation can be reduced by collecting those batches into a dome with a 36-fold greater capacity. As a result, segregation in small capacity silos may be negligible as compared to larger silos and domes. A Frequency Domain Analysis (FDA) was performed based on this assumption. The CA models developed by Dissanayake et al [9] is used to conduct this test. It is expected to identify critical handling steps in a wood pellet handling chain that may have a significant impact on material segregation.
The methodology, results and discussion, as well as a conclusion to the study, are provided in the following sequel.

2. Methodology

A simplified representation of a typical wood pellet handling chain, based on operations at a UK power generation facility, is shown in Figure 1. The chain includes multiple transfer and storage stages, beginning with ship unloading, followed by screw conveyors and belt conveyors that transport the material to a series of large silos (each with a 30,000-tonne capacity). From there, pellets are transferred to a smaller 2,500-tonne rail load-out silo and then transported by rail to a second facility at a different location. At the receiving end, the material is stored in four domes, each with a 90,000-tonne capacity, before being transferred to a day silo and eventually fed into the mill and furnace.

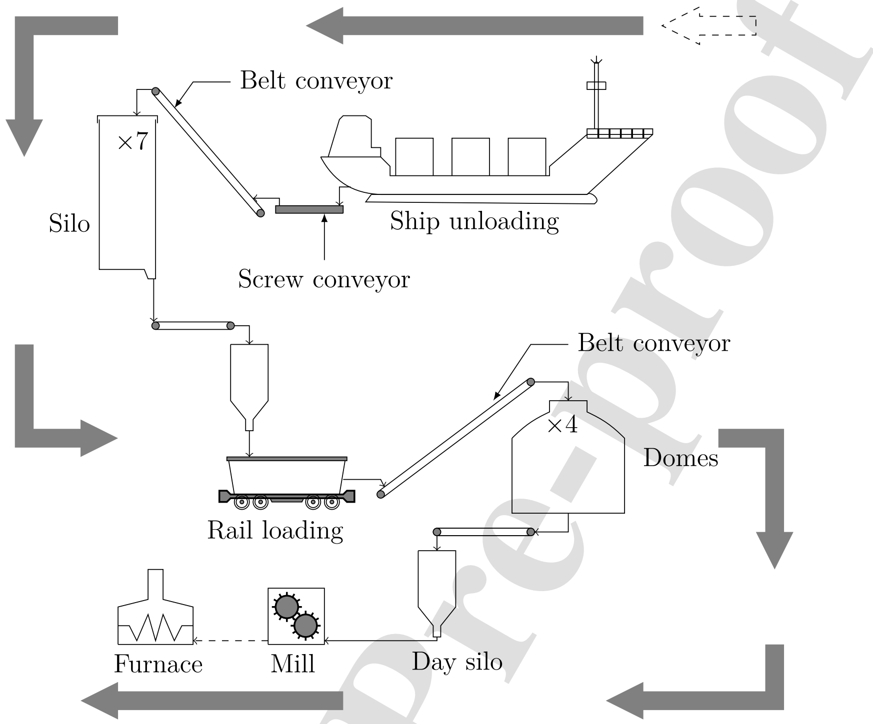


Figure 1: Different transfer points in a chain of wood pellet handling system

This layout illustrates the multi-stage nature of industrial biomass logistics and forms the basis for identifying key segregation contributors using Cellular Automaton modelling and FDA.

2.1. Frequency Domain Analysis for Segregation Assessment

To apply Frequency Domain Analysis (FDA) for segregation assessment, it is essential to begin with a simple case study. However, before introducing the case study, the discharge behaviour of silos must be studied, particularly the core-flow discharge pattern, which is predominant in large industrial silos.

Core-flow is the default flow pattern in silos that are not specifically engineered with flow characteristics in mind. Factors such as hopper angle, wall material, and surface friction all influence whether core-flow occurs [29]. When the hopper angle is too short or the hopper wall friction exceeds the materials internal shear stress, the material fails to slide down along the walls. Instead, flow initiates through a central channel directly above the outlet, driven primarily by gravity.

As discharge continues, a narrow flow channel propagates upward through the material bed; this is referred to as upward void propagation [9]. Once the flow channel reaches the top surface, and if the material is sufficiently free-flowing, the top layer begins to funnel into the

main stream; a process known as funnelling. Throughout this flow process, material near the silo walls remains largely stagnant [29].
Figure 2 illustrates the core-flow pattern. The darker regions in the figure indicate stationary zones within the silo [9, 29]. This discharge mechanism results in a first-in, last-out flow behaviour [29, 30], which has significant implications for segregation. Notably, fines that tend to accumulate near the centre because of sieve/percolation segregation [31] of the silo are discharged first, followed by coarser particles. This leads to abrupt spikes in fines content during the early stages of discharge.

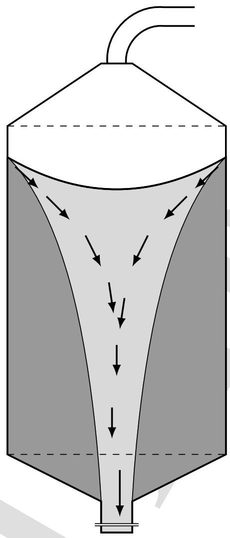


Figure 2: Flow pattern of a core-flow silo

An important consequence of core-flow behaviour is its first-in, last-out discharge characteristic [9, 29, 32].
Consider a scenario where a silo is filled in two equal halves: the first half with low fines content and the second half with significantly higher fines content. As a result, coarser particles tend to settle in the lower layer, while finer particles accumulate in the upper layer of the silo. Due to the core-flow discharge pattern typical of flat-bottom silos, the upper fines-rich layer, which is added last, exits first, as illustrated in Figure 2. Consequently, more coarse material is discharged during the second half of the discharging process, consistent with the first-in, last-out behaviour of core-flow systems.
Consequently, the initial discharge phase will exhibit a sharp spike in fines content, followed by a gradual decline as coarser material is released from the lower half. This theoretical discharge pattern is illustrated in Figure 3.

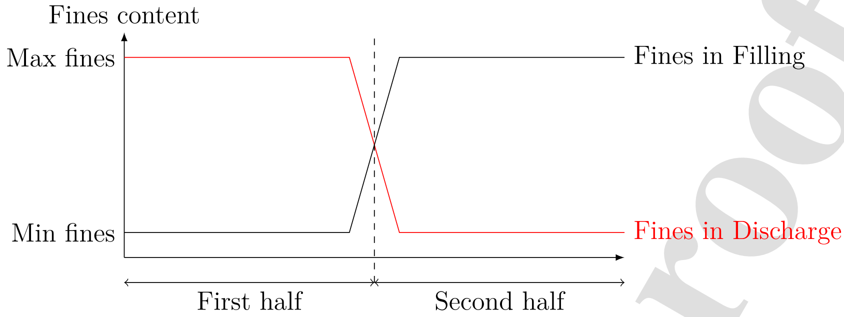


Figure 3: Fines content in variation in discharge with respect to variation of inflow fines content.

As illustrated in Figure 3, the first half of the filling contains a low fines content. However, due to the core-flow discharge pattern, the initial stage of discharge exhibits a higher fines concentration, indicating that the discharge pattern behaves as an approximate inverse of the inflow profile. If the test is repeated with a reversed inflow, where the first half has high fines content and the second half has low fines, the resulting discharge curve would show low fines initially, followed by an increase in fines during the second half of discharge.

If the time required to fill a silo is considered a single period, then the variation in fines content during that time can be interpreted as a frequency signal. Likewise, the complete discharge of the silo can be viewed as another period, with its own fines variation signal. The amplitude of each signal corresponds to the difference between the maximum and minimum fines content. This analogy allows user to conceptualise the silo as a generator of frequency signals.

Figure 3 illustrates a fines profile during filling, which can be interpreted as a representative signal for a single filling event. To regard a silo as a signal generator, it must produce an oscillating output signal even when the input is steady. Consider a scenario where the silo is filled with a homogeneous mixture of fines and coarse particles; a steady signal with minimal variation. Due to segregation during filling, the internal distribution of particles becomes non-uniform. Upon discharge, particularly in a core-flow silo, a pronounced spike in fines content typically appears at the beginning, followed by a drop towards the end. Even in mass-flow silos that minimise segregation during discharge, significant variation in fines concentration can still emerge due to prior segregation. From this perspective, a silo transforms a steady input into a variable output, effectively generating an oscillating signal. This behaviour justifies the treatment of the silo as a frequency generator, forming the conceptual foundation for the FDA. Figure 4 illustrates this concept for a core-flow silo.

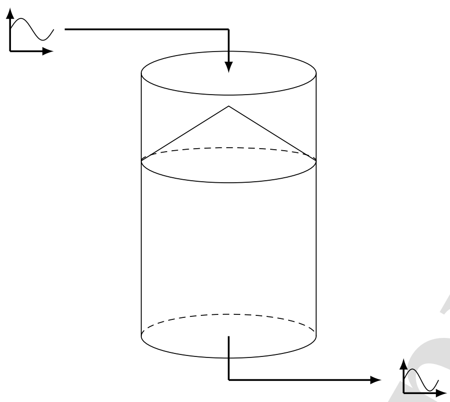


Figure 4: Silo as a signal generator

A time domain graph typically shows how a signal varies over time, with time measured in seconds (s) and frequency in Hertz (Hz). In contrast, a frequency domain graph represents how much of the signal lies within each given frequency band over a range of frequencies. To analyse the frequency characteristics of a signal, a mathematical transformation such as the Fourier Transform can be used. This transformation decomposes a time-based signal into its constituent frequencies, allowing the identification of dominant oscillatory components [33, 34, 35]. In the context of this study, the variations in fines content during discharge are treated as signals, and the use of the FDA enables the extraction of dominant segregation patterns. However, at present, the FDA is not used in industry, as it is a novel theoretical method proposed in this study to identify segregation patterns.
To demonstrate this concept, a simplified case study is presented in the following section.

2.2. Case study – Theoretical Explanation of Silo as a Signal Generation

To illustrate the conceptual application of the FDA, this study considers a scenario in which fines content varies during a single silo filling cycle. Since direct quantitative data is not available, the analysis uses normalised qualitative observations of fines variation to construct representative sine functions. These functions offer a simplified approach to quantify the changing fines content during material inflow. For example, a frequency of 1 represents a single smooth variation during one complete filling cycle, where the fines content starts at an average level, gradually decreases to a minimum, increases to a maximum, and finally returns to the average fines level. In contrast, a frequency of 5 represents five such fluctuations within the same filling cycle, indicating more dynamic changes in fines content over time. The minimum and maximum fines contents are represented by integers 1 and 10, respectively, in the CA modelling concept discussed in Dissanayake et al. [9]. These integer values can be converted back to actual fines percentages using an appropriate calibration curve.
Figure 5 illustrates the idealised input patterns corresponding to frequencies 1 and 5 within a single silo filling period. Although the current study does not include empirical data,

this normalisation method provides a theoretical framework to examine how the temporal structure of fines variation may influence segregation.

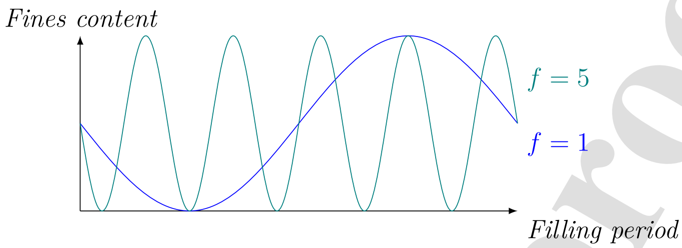


Figure 5: Filling frequencies

As previously explained, and based on the filling frequencies shown in Figure 5, the first scenario with a filling frequency of 1, results in the formation of two distinct layers: a coarse material layer at the bottom and a concentrated fines layer at the top of the silo. In contrast, the scenario with a filling frequency of 5 produces multiple alternating layers of coarse and fine particles. Figure 6 illustrates the resulting deposition patterns for these different inflow frequencies. In the figure, dark regions represent fines-rich layers, while light regions indicate coarse-dominated layers.

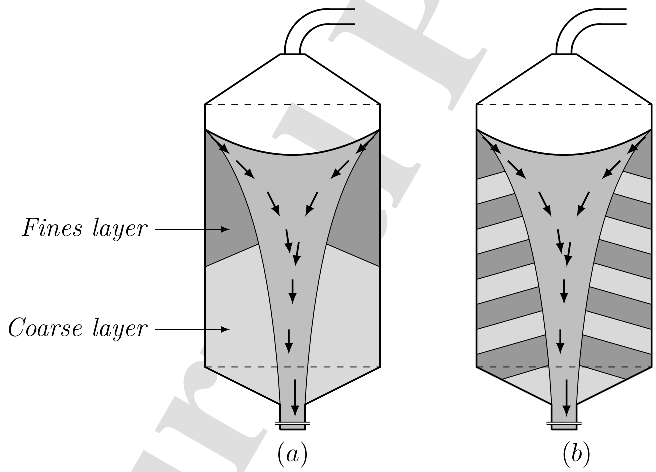


Figure 6: (a) Low frequency filling (frequency =1) (b) High frequency filling (frequency =5)

The discharge from silo (a) in Figure 6 exhibits a distinct two layers: a higher fines concentration is released during the first half of the discharge, followed by a significantly lower fines concentration in the second half. This sharp transition reflects the filling configuration with clearly separated fines-rich and coarse layers, and results in a waveform with smooth,

wave-like features.
In contrast, silo (b) demonstrates the typical behaviour of core-flow (or funnel-flow) discharge, where only the central core flows while material along the walls remains stagnant. As the flowing channel intersects multiple deposited layers, this pattern inherently induces axial and radial mixing between fines-rich and coarse regions. The resulting discharge composition is more blended, with a gradual variation in fines content, rather than abrupt changes. This phenomenon has been theoretically explained by Schulze [29] and supported by more recent work such as Huang et al. [36]. As the number of deposited layers increases, the mixing effect becomes more pronounced, producing a smoother discharge curve that resembles a sinusoidal profile, rather than a sawtooth.
It is evident that higher filling frequencies lead to increased mixing during silo discharge compared to lower frequencies. As the filling frequency increases, the amplitude of the discharge signal becomes damped, gradually aligning with the silos average fines content. With further increases in frequency, this damping effect becomes more dominant, reducing the signals variability.
This behaviour resembles the operation of a Low-Pass Filter (LPF) in electronic systems. An LPF allows signals with frequencies below a certain cut-off to pass through while attenuating those above the threshold [37]. A similar filtering effect is observed in the silo: high-frequency fluctuations in fines content are increasingly suppressed during discharge.

2.3. Method to Evaluate Mixing at Different Filling Frequencies

Previous observations suggest that higher filling frequencies enhance the separation of layers during silo filling, while the core-flow discharge mechanism tends to mix these layers during discharge. To quantitatively evaluate the extent of mixing at different filling frequencies, a simple experimental method can be applied.
First, the silo is filled using a predefined input fines frequency, represented by a sine wave with characteristic fines rising and falling trends. The fines content in the discharge is then recorded as a function of discharge period. Next, the silo is filled using the inverse of the original input signal i.e., an inverted sine wave with a 180° phase shift, resulting in a mirrored layering pattern within the silo. This discharge profile is also recorded.
To determine the degree of mixing induced by the discharge process, the Root Mean Square (RMS) difference between the two discharge curves is calculated, as shown in Equation 1.

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(D_{\text{sine},i} - D_{\text{inv},i}\right)^2} \tag{1}$$

Where :

- N is the length of the arrays,
- $D_{\text{sine},i}$ is the i^{th} value of the discharge from the sine array,
- $D_{\text{inv},i}$ is the i^{th} value of the discharge from the inverted sine array.

A lower RMS value suggests higher mixing (i.e., more similar discharge curves), while a higher RMS value indicates greater preservation of the initial layering and less mixing during discharge. If the silo induces mixing during discharge, the RMS value should be negligible; otherwise, it will be relatively high.
To cover all potential scenarios, the silo should be filled and emptied at Input frequencies of 0.25, 0.5, 1, 2, ..., up to 10. A simple case study can further illustrate this method.

2.4. Case Study – Simulation Study

Consider the following simulation study. In this simulation the filling frequency '1' is used. Then the sine and inverted sine curve shape of inflow curves can be shown as following Figure 7.

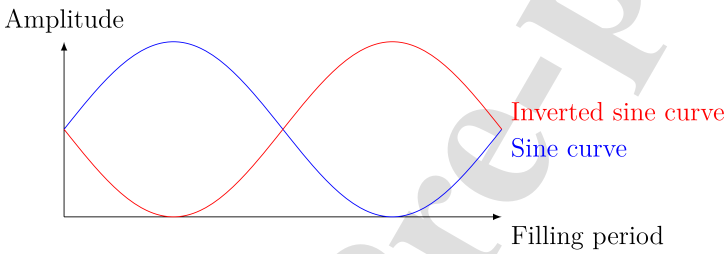


Figure 7: Filling Frequencies

In the Cellular Automaton (CA) model developed by Dissanayake et al. [9], a discrete numerical scale ranging from 0 to 10 was implemented to represent fines content and particle size distribution (PSD) within each cell. Here, a value of 0 denotes an empty cell, 1 corresponds to a cell entirely filled with coarse particles (i.e., clean pellets), and 10 signifies a cell fully saturated with fines. Based on the CA models governing rules, inflow signals such as sine and inverted sine waveforms, as shown in Figure 7, can be digitised to construct the models input profiles. The resulting fines distribution patterns generated by the simulation are shown in Figure 8.

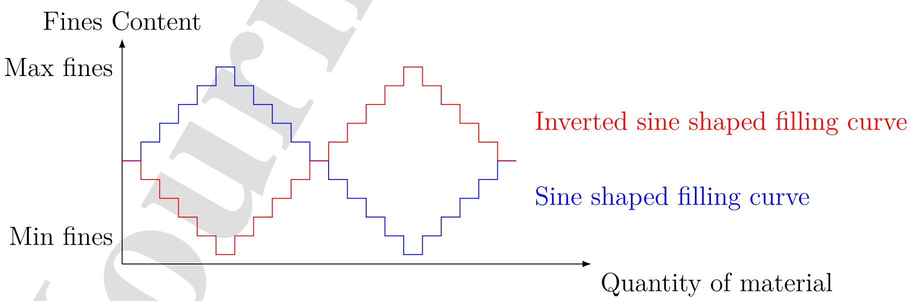
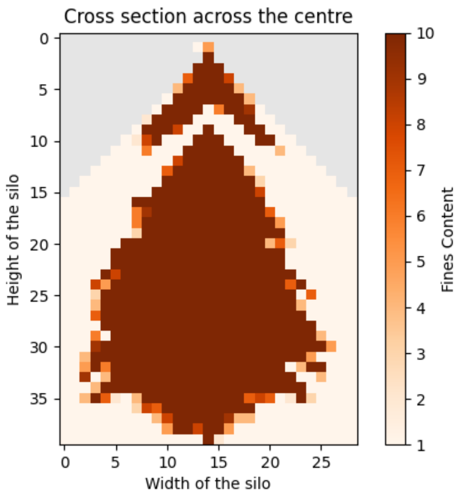
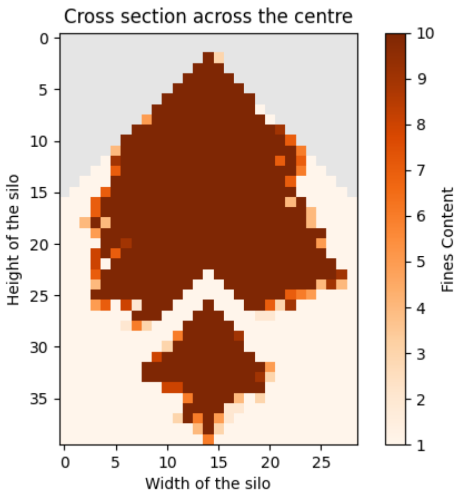
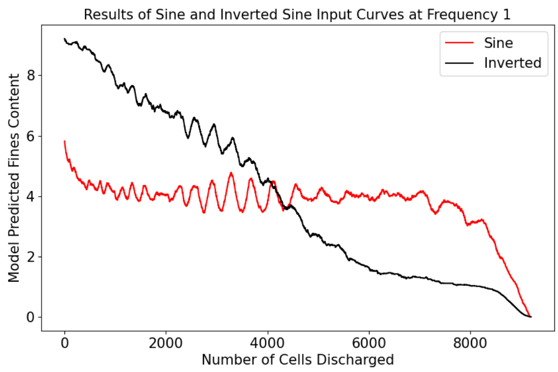


Figure 8: Digitised input curves.

Simulation of this particular scenario can be summarised as in the following table; Table 1.

Table 1: Simulation Case Study: Evaluation of Mixing Using RMS Values at Filling Frequency = 1

Filling Frequency	1
Number of Cells in Filling	16,000
Cross Section of Domain (Sine-Shaped Filling)	

Cross Section of Domain (Inverted Sine-Shaped Filling)	
Number of Cells Discharged	10,000
Output Curves for Sine and Inverted Sine Fillings	
Expectation	It is expected that if the silo induces mixing during discharge, the Root Mean Square (RMS) value between the two output curves (from sine and inverted sine fillings) will be minimal. The RMS value quantifies the degree of similarity or difference between the discharge profiles.

Comment	A substantial difference between the two output curves indicates pronounced layering within the silo. This suggests that both sine-shaped and inverted sine-shaped filling patterns significantly influence segregation, leading to the formation of distinct layers and resulting in clearly observable segregation during discharge.

In this study, simulations were carried out for all proposed frequencies (0.25, 0.5, 1, 2, ..., 10) using both sine-shaped and inverted sine-shaped inflow signals. The amplitude of each signal was quantified using the root mean square (RMS) method, as defined in Equation 1. The output amplitudes were similarly evaluated, and their difference from the inputs was used to calculate the ratio, which was then expressed in decibels (dB) using a logarithmic relationship given in Equation 2:

$$dB = 20 \times log_{10}\left(\frac{A_{output}}{A_{in}}\right) \tag{2}$$

Here, A' denotes the amplitude. Once the decibel values are calculated for each case, a frequency response plot can be constructed as as shown in Figure 9 by plotting decibels on the y-axis against filling frequency on the x-axis. From this plot, the cut-off frequency can be identified as the point beyond which signal attenuation becomes pronounced. Figure 9 illustrates the expected trend, demonstrating the characteristic low-pass filter behaviour and the location of the cut-off frequency.

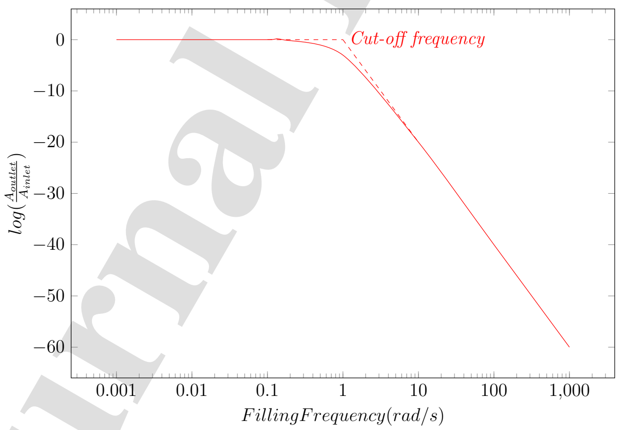


Figure 9: Theoretical low pass filter

Identifying the cut-off frequency allows for a more targeted understanding of segregation dynamics in material handling. If the filling frequency at a particular silo exceeds the cut-off frequency, it suggests that significant internal mixing occurs during discharge, effectively dampening the variation in fines content. Consequently, such scenarios can be classified as non-critical, and optimisation strategies can focus on other points in the process where segregation is more prominent.

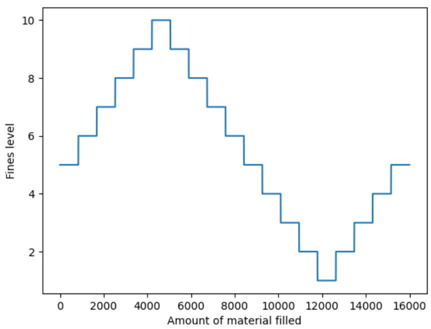
3. Results and Discussion

To evaluate the effect of different filling frequencies on discharge mixing, predefined inflow signals were implemented within the CA simulation domain. These signals modelled as sine and inverted sine curves were used to control the fines content distribution during the filling process. The logic for generating these inflow patterns was developed in Python, ensuring temporal accuracy and fines stratification. The pseudo code for clear understanding is provided in Algorithm 1.

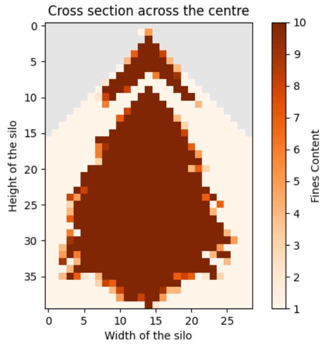
Algorithm 1 Create Inflow Fines Curve

```
Require: filling_frequency
Ensure: fines_in_inflow, fines_in_inverted_inflow
pattern ← [5, 6, 7, 8, 9, 10, 9, 8, 7, 6, 5, 4, 3, 2, 1, 2, 3, 4, 5]
inverse_pattern ← REVERSE(pattern)
fines_in_inflow ← REPEAT(pattern, filling_frequency)
fines_in_inverted_inflow ← REPEAT(inverse_pattern, filling_frequency) return fines_in_inflow, fines_in_inverted_inflow
```

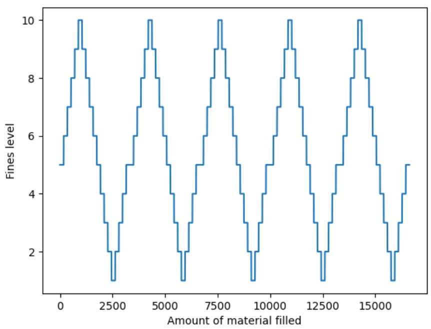
Upon completing a single filling cycle at varying frequencies, the simulation domain characterised by spatial variations in fines concentration was analysed through cross-sectional inspection. Figure 10 illustrates representative cross-sections across the silo diameter for filling frequencies of 1 and 5. Darker regions indicate areas of fines accumulation, while lighter regions represent zones with lower fines content.



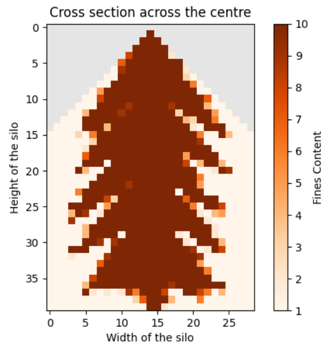
(a) Frequency 1 filling curves



(b) Cross Section of the domain for frequency 1 filling



(c) Frequency 5 filling curves

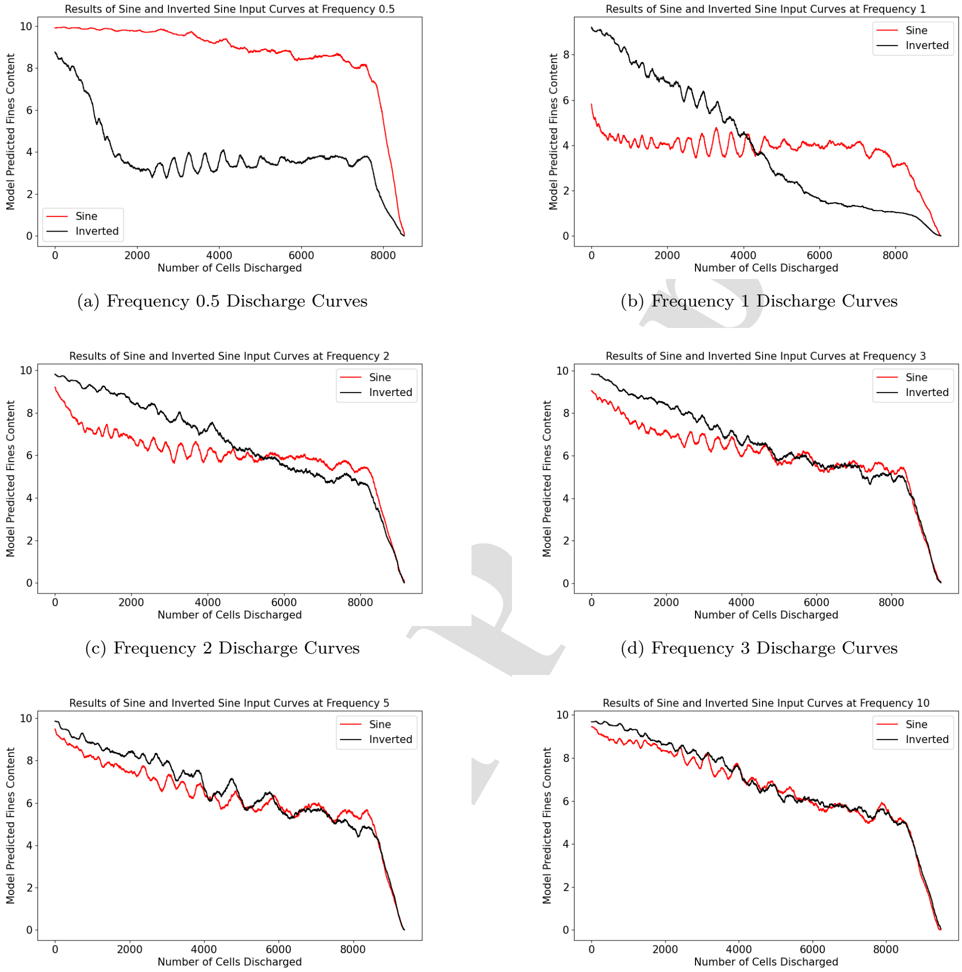


(d) Cross Section of the domain for frequency 5 filling

Figure 10: Corss sections of simulation domain at different frequencies of filling

In Figure 10, distinct regions of high and low fines accumulation inside simulation domain can be clearly observed. In subfigure 10b, two prominent fines layers are visible. When compared with the inflow frequency curve shown on the left subfigure 10a, it becomes evident that regions with high fines content accumulate first, followed by zones with little or no fines, and then a gradual increase in fines content. Similarly, in the case of higher filling frequencies, the results reveal five clearly defined fines layers, corresponding to the input signal characteristics.
Following Figure 11 shows discharge fines variation for different filling curve; sine and inverted sine curve fillings. The variations are plotted against the number of cells discharged. In the CA framework, each cell represents a discrete volume of material with a defined fines concentration. Tracking the number of cells discharged over time provides insight into how segregation patterns evolve throughout the discharge. This approach allows the dynamic behaviour of fines and coarse particles to be monitored in a computationally efficient and

interpretable manner [9].



(a) Frequency 0.5 Discharge Curves

(b) Frequency 1 Discharge Curves

(c) Frequency 2 Discharge Curves

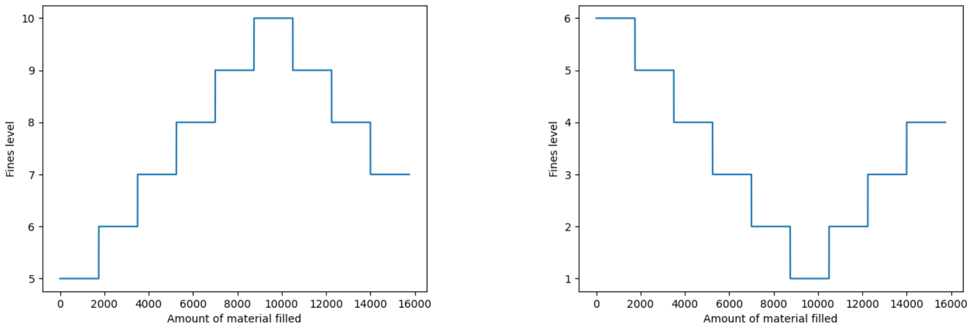
(d) Frequency 3 Discharge Curves

(e) Frequency 5 Discharge Curves

(f) Frequency 10 Discharge Curves

Figure 11: Discharge curves for sine and inverted sine input frequencies

According to the Figure 11, at lower filling frequencies, the discharge curves show significant deviation and are strongly influenced by the shape of the inflow fines profile. For example, subfigure 13a presents the output fines content for sine shaped and inverted sine shaped inflow signals shown in Figure 12 at a frequency of 0.5. When the filling follows an inverted sine profile shown in subfigure 12b in Figure 12; starting with high fines content that gradually decreases, fines accumulate predominantly at the beginning of the filling cycle. However, due to the symmetrical nature of the signal, some fines also accumulate toward the end. Given the first-in, last-out discharge behaviour of silos, this results in an initial sharp drop in fines during discharge. Conversely, the regular sine-shaped filling, which begins with low fines content, increases to a peak in mid-cycle, and then decreases again, results in a reverse deposition pattern. As a result, the discharge curve for the sine-shaped filling illustrate the mirror effect relative to the inverted sine case.

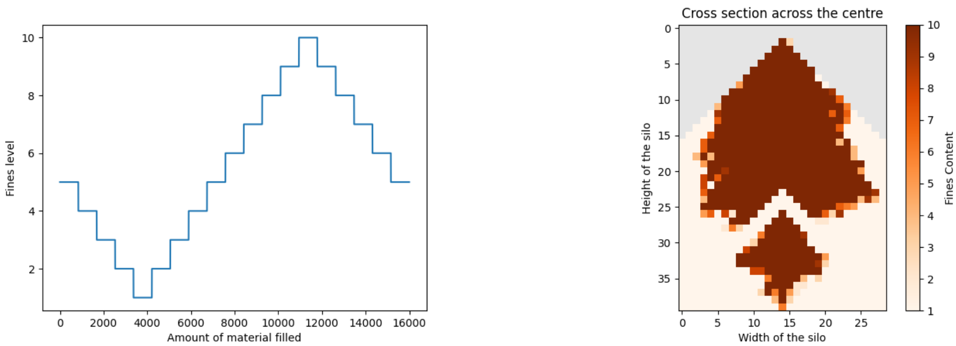


(a) Frequency 0.5 sine shaped filling curves

(b) Frequency 0.5 inverse sine shaped filling curves

Figure 12: Corss sections of simulation domain at different frequencies of filling

Figure 13 shows side by side comparison with the digitised invert sine shaped inflow curve with the simulation results for filling frequency 1. As the fines level initially decreases step by step, then rises to a peak before tapering off, the simulation clearly reflects this behaviour, showing lower fines accumulation at the beginning and higher fines concentration toward the end of the silo.



(a) Frequency 01 filling curves

(b) Cross Section of the domain for frequency 01 filling

Figure 13: Corss sections of simulation domain at different frequencies of filling

In this analysis the filling frequencies were chosen to cover most of the common scenarios could observe in filling of silos. '0.25' is the minimum frequency could generate. filling frequency '10' is chosen to cover the upper limits. Following table, 2 summarise simulation study and calculation of RMS values, dB values with respect to the inflow frequencies. The RMS values of the inflow curves are rather consistent. In Table 2, the RMS values of the outflows vary substantially.

Table 2: FDA for different filling frequencies

Filling frequency	RMS in inflow	RMS outflow	dB
0.25	2.9	3.07	0.50
0.5	5.1	4.5	-1.09
1	5.0	2.34	-6.60
2	5.0	1.08	-13.31
3	5.0	0.7	-17.08
4	5.0	0.59	-18.56
5	5.0	0.52	-19.66
6	5.0	0.43	-21.31
7	5.0	0.38	-22.38
8	5.0	0.36	-22.85
9	5.0	0.32	-23.88
10	5.0	0.31	-24.15

Using the data presented in Table 2, a frequency response plot was generated, as shown in Figure 14. The dashed line represents the best-fit trend through the decibel values. The resulting curve closely resembles the characteristic shape of a Low Pass Filter (LPF). To determine the corner frequency, the best-fit line is extrapolated to intersect the zero-decibel line. Based on this intersection, the estimated corner frequency is ≈ 0.5, as indicated in the Figure 14.

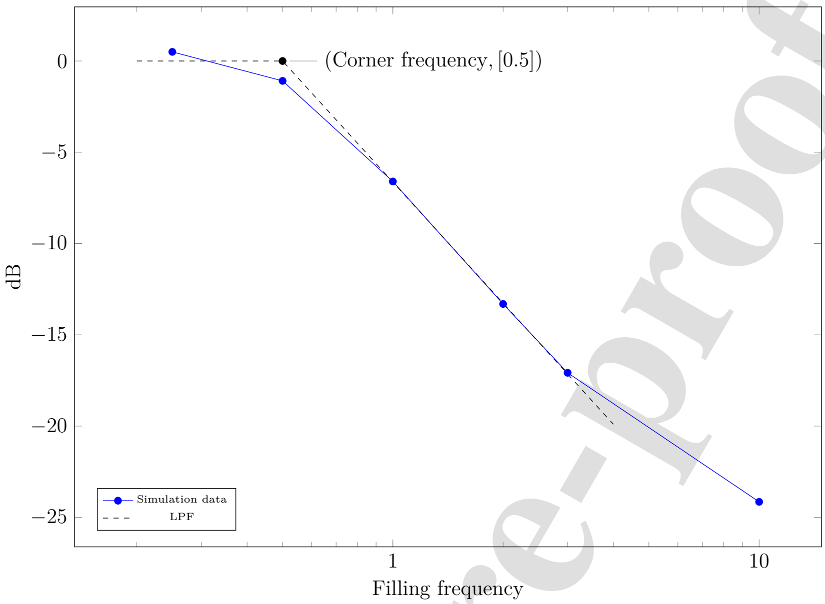


Figure 14: Low pass filter for silo discharging

The chosen silos at the port will generate a fines variation at a frequency of '1' cycle per 25,000 tonnes (1/25000) assuming that the usual storing capacity of 25000 tonnes out of 30000 total capacity. The corner frequency of the rail load-out silos is '0.5' per 2500 tonnes, i.e., 1 cycle per 5000 tonnes. The port bulk silo generates frequencies much lower than the rail load-out silo corner frequency; the bulk silo output fines variation will run straight through the rail load-out silo into the trains unattenuated.

However, the rail load-out silos themselves, discharging in core flow, will introduce a frequency of 1/2500. Considering the 90,000 tonnes storage domes at the power plant, although there are 14 outlets, each outlet can potentially activate 1/5 of the dome contents of 90,000 tonnes, would give 18,000 tonnes. Corner frequency of such situation would be $0.5 \times 1/18000$ tonnes i.e., 1/36000. The rail load-out generated frequency of 1/2500 is about 14 times higher than the dome corner frequency, so referring to Figure 14, at a frequency 14 times the corner frequency i.e. frequency of 7' the input signal is diminished by -22 dB, i.e., practically disappears.

However, the port bulk silo generated frequency of 1/25000. If the dome discharge corner frequency is 1/36000 then the port bulk silo frequency at 1/25000 is approximately 1.4 times higher than the dome corner frequency. Therefore, referring to figure 14 at a frequency 1.4' times the corner frequency i.e 0.7' frequency the damping is approximately, -3dB, which is significant.

If the domes were completely filled and emptied during each cycle, their characteristic frequency equivalent to one cycle per 90,000 tonnes that would be significantly lower than

that of the port silos. Consequently, any segregation effects originating from the port silos would be further attenuated. However, such complete fill-empty cycles are not standard operational practice.
Based on the FDA, it is evident that segregation intensity originating from the port silos is partially attenuated, while the dome at the plant exhibits the most pronounced segregation effects. Although the rail load-out silo may contribute to segregation, its influence is negligible at the dome outlet. Consequently, the handling stages from the rail load-out silo to the dome including transport by train can be excluded from detailed simulation, reducing the complexity of the analysis.
Similarly, segregation between the ship and the port 30,000-tonne silo is minimal due to the buffering effect of the large storage volume. Any intermediate handling before or after this point has a limited impact, especially since materials are eventually transferred into even larger domes at the plant. This indicates that segregation effects become negligible once the material is collected into sufficiently large storage units.
However, the filling and discharge behaviour of large silos such as the 30,000-tonne silo at the port cannot be entirely disregarded. These units may still influence downstream fines distribution and should therefore be considered in any optimisation strategy. Among all components, the dome's filling and emptying patterns exhibit the strongest influence on segregation at the outlet, making it the most critical unit to address in the optimisation of material discharge.

4. Conclusion

This study aimed to identifying main segregation contributor in a material handling chain specially in wood pellet handling. Due to the complex nature of pellet handling systems comprising multiple transfer points such as ship unloading, intermediate storage in port silos, train transport, and final storage in domes fully modelling each stage would compromise the goal of creating a fast, computationally efficient simulations.
To address this, a Frequency Domain Analysis (FDA) method was used to distinguish the main segregation contributors from less significant ones. This approach draws inspiration from low-pass filters in electronics but is adapted to use in the frequency domain of granular flow modelling. By simulating inflow signals with frequencies ranging from 0.25 to 10 and converting output amplitudes to decibel values, a clear LPF-like response curve was established. The corner frequency was determined to be 0.5, serving as a quantitative threshold for identifying impactful segregation stages.
The analysis revealed that segregation effects from the port bulk silos are partially attenuated and therefore less influential than those from the dome. In contrast, segregation from the rail load-out silos was found to have a negligible effect at the dome outlet and can be excluded from optimisation efforts. These insights enable a streamlined simulation strategy by focusing only on critical transfer points most notably, the dome itself which was shown to exhibit the greatest influence on fines concentration at the discharge point.
Overall, this work contributes a novel, FDA based framework for simplifying segregation modelling in large-scale pellet handling operations, supporting more effective and efficient

optimisation of material discharge strategies.
It is important to note that the findings presented in this study are based solely on simulation and theoretical analysis; while grounded in a previously validated CA framework, further experimental validation of the FDA results is required to confirm their broader applicability.

CRediT Authorship Contribution Statement

Susantha Dissanayake: Conceptualisation, Methodology, Investigation, Formal analysis, Writing-original draft. **Ghofran Salah:** Formal analysis, Writing-review & editing. **Hamid Salehi:** Formal analysis, Writing-review & editing. **Stefan Zigan:** Supervision, Formal analysis, Writing,-review & editing. **Tong Deng:** Supervision, Formal analysis, Writing,-review & editing. **Michael Bradley:** Conceptualisation, Funding acquisition, Supervision, Writing-review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Highlights

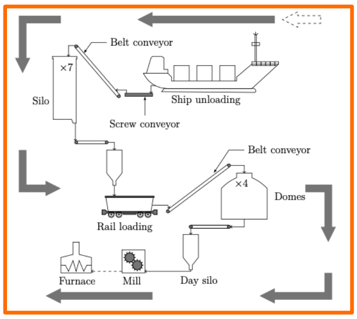
Frequency Domain Analysis for Identifying Dominant Segregation Units in a Chain of Material Handling Processes: A Cellular Automaton Framework

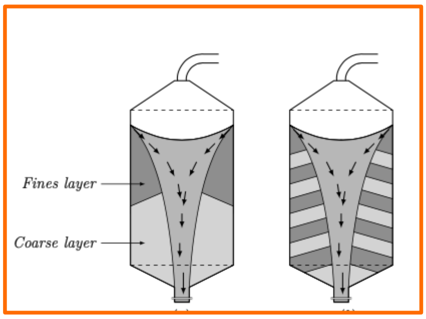
- A novel Frequency Domain Analysis (FDA) approach identifies dominant segregation units in pellets handling chains, based on validated Cellular Automata (CA) models.
- FDA analysis indicates that segregation in smaller silos (2,500 tonnes) is negligible when materials are transferred to larger storage units (90,000 tonnes).
- The FDA method reduces simulation complexity by eliminating the need for full-chain modelling, providing a novel computationally efficient alternative for predicting segregation.

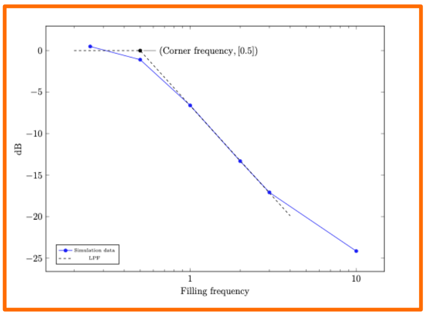
Frequency Domain Analysis for Identifying Dominant Segregation Units in a Chain of Material Handling Processes: A Cellular Automaton Framework

Frequency Domain Analysis for Identifying Dominant Segregation Units in a Chain of Material Handling Processes: A Cellular Automaton Framework

A novel Frequency Domain Analysis to identifies dominant segregation contributors in a chain of material handling







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CA modelling

Declaration of interests

☐ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☒ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Susantha Dissanayake reports financial support was provided by Net Zero Research. Susantha Dissanayake reports a relationship with Net Zero Research that includes: funding grants. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.