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OPTIMIZATION OF HOPPER DESIGN BY GENETIC ALGORITHMS

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Abstract

In the handling of particulate matters, hoppers are frequently used as intermediate storage, but during their filling and emptying, particle size segregation may occur. The hopper geometry is known to affect the outflow pattern (mass flow or funnel flow), and possible inserts in the hopper can also affect the patterns and particle segregation. The present work studies the size segregation in hopper by discrete element modeling (DEM). Due to the considerable computational effort required by the numerical technique, a factorial plan was applied to design a set of DEM experiments, where the insert geometry and position were varied. The results form the basis for a black-box modeling, where the outflow patterns were described by a neural network. Using the arising neural model, the geometry was optimized using genetic algorithms with respect to particle segregation of the outflow. The most promising solution was finally verified by DEM modeling. Thus, by the proposed method complex design problems can be tackled avoiding excessive computational burden.

Key words: hybrid modeling, particulate flow, size segregation, optimal design, discrete element method, neural networks, genetic algorithms

1. INTRODUCTION

The handling and processing of granular solids are vital operations in a wide range of industries. It has been estimated that roughly 50% of the products and at least 75% of raw materials in industry are granular (Nedderman 1992, Zhou and Ooi 2009). Granular solids are commonly stored in hoppers of different types, particularly in the mining, cement and base metals industries. A primary requirement for hopper design is that mass flow should occur during discharge. However, most hoppers do not show consistent flow, but exhibit funnel flow during discharge which induces particle segregation. To alleviate this problem, rigid objects called flow corrective inserts are sometimes used inside hoppers, such as conical inserts, bullet inserts and cone-in-cone inserts (Johanson 1986, Tang and Puri 2004). Johanson (1967) proposed a method to determine the position and scale of conical inserts as well as methods for estimating the pressure on the insert and also suggested that a flow corrective insert of an appropriately chosen shape placed at a certain critical height above the hopper outlet may reduce the size of stagnant zones. Although the above studies yield useful guidelines for the design of inserts, a rigorous optimizing of their position and scale has not been reported, and, in particular, not for suppressing size segregation during discharge.

From its original development by Cundall and Strack (1979), the discrete element method (DEM) has become a feasible numerical method for analyzing discontinuous media. The technique has been applied to simulate different granular flows in the industries, including drum mixers (Stewart et al.

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2001), fluidized beds (Kaneko et al. 1999) and hopper charging and discharging flows (Li et al. 2008, Chou et al. 2009, Nguyen et al. 2009). Different hopper types have been studied, including cylindrical hoppers (Zhu and Yu 2005), bin hoppers (Chou et al. 2009) and wedge-shaped hoppers (Ketterhagen et al. 2008). Cleary et al. (2002) analyzed the role of particle shape and interparticle cohesion on the discharge process and concluded that 2D simulation by DEM could be useful for equipment design. Ketterhagen et al. (2008, 2009) used DEM to study material flow and size segregation during discharge of wedge and conical hoppers and found a relation between the macroscopic friction angle and the microscopic friction coefficient. Yu and Saxén (2010) focused on size segregation of ternary size pellets during hopper discharging and confirmed DEM results by experiments.

The above studies demonstrate that DEM can provide interesting information and that the modelling technique holds promise for future applications. However, its computational burden still limits large-scale studies and applications, e.g., design tasks where the DEM problem has to be solved repetitively. In the present work, we propose a procedure for using DEM in design and illustrate it by optimizing a conical insert with respect to position, shape and size of the insert in a hopper to minimize size segregations of ternary size particles during the discharging process. The tools used are described in the next section, the hybrid procedure in section three followed by the results in section 4. Finally, some conclusions are presented in the last section.

2. COMPUTATIONAL METHODS

Due to the considerable computational effort required by DEM, it is not usually feasible to optimize geometrical parameters with a DEM sub-problem for the objective function. Therefore, another procedure was adopted: A set of DEM experiments of ternary size particle flow from a hopper with different insert parameters (size, shape and position) was simulated, and the mass fractions of the three particle sizes were registered in the outflows. These results were next approximated by neural networks, with the aim to obtain a model that can be executed rapidly enough for advanced optimization purposes. The arising model was then used to find the insert parameters that would lead to minimum particle segregation at hopper discharge by applying a multi-objective genetic algorithm. Finally, some potential solutions were selected and the results were finally verified by DEM simulation.

2.1. Discrete Element Method (DEM)

Moving particles in a granular system undergo translational and rotational motions which can be described by Newton's second law of motion. In the DEM, an interparticle contact model is used (cf. figure 1) composed of spring and dashpot, which correspond to the elastic and plastic nature of particles in the normal direction, respectively. In the tangential direction, the model consists of slider, spring and dashpot. The governing equations for a particle (i) interacting with another particle (j) can be written as (Zhou et al. 2008)

$$\mathrm{m}_i \frac{du_i}{dt} = \sum_{j=1}^{K} (F_{\mathrm{cn},ij} + F_{\mathrm{dn},ij} + F_{\mathrm{ct},ij} + F_{\mathrm{dt},ij}) + m_i g \quad (1)$$

$$I_i \frac{\mathrm{d}\omega_i}{\mathrm{dt}} = \sum_{j=1}^{K} (T_{\mathrm{t},ij} + T_{\mathrm{r},ij}) \quad (2)$$

where u_i, I_i and ω_i are the translational velocity, moment of inertia and angular velocity of particle i, respectively. The forces involved are the gravitational force ($m_i g$) and interparticle forces between the particles, which include the normal force and tangential contact force, $F_{\mathrm{cn},ij}$ and $F_{\mathrm{ct},ij}$, and damping forces, $F_{\mathrm{dn},ij}$ and $F_{\mathrm{dt},ij}$.

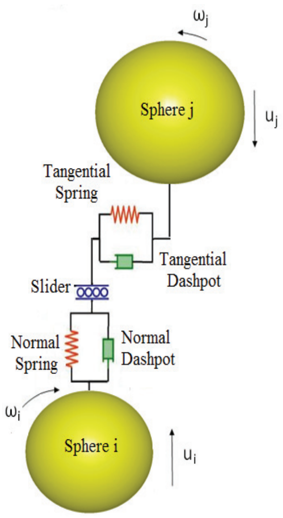

Fig. 1. DEM modelling principle.

The inter-particle forces are summed over the K particles in contact with particle i. Torques acting on particle i include tangential force, $T_{\mathrm{t},ij}$ and rolling friction force, $T_{\mathrm{r},ij}$. The hardness of the particles and the dashpot are related to the Young's modulus and the coefficient of restitution, respectively. The friction between entities is defined with a Coulomb-type of friction law. DEM tracks the motion of all particles considering their interaction with other particles or boundaries. Eqs. (1) and (2) give the particle movement and the particles' positions are obtained by integration.

2.2. Artificial Neural Networks (ANN)

Neural network models have gained wide popularity for solving nonlinear problems, including regression and classification tasks, in a variety of application fields. Theoretical analysis has shown that a feed forward neural network with one hidden layer of nonlinear (e.g., sigmoid) nodes and a linear output node is able to approximate an arbitrary continuous (and twice differentiable) bounded function to any accuracy, given enough capacity, i.e., a sufficient number of hidden nodes (Cybenko 1989). In this study, standard sigmoids $y(x) = 1/(1+\exp(-x))$ are used for the hidden nodes while linear relations are used in the output layer of the networks studied. The networks were modeled by the Matlab Neural network toolbox.

2.3. Genetic Algorithms (GA)

Genetic algorithms are optimization techniques based on the concepts of natural selection and genetics (Holland 1975) that work with a group of candidate solutions, called the population, evolving through time like a natural population of species. Each individual (chromosome) of the population represents a solution to the optimization problem and is described by a sequence of genes, which usually code to the unknown variables to be determined. The search involves three components: selection, crossover, and mutation. For each generation the individuals are evaluated by a fitness (objective) function and are typically reproduced in proportion to their fitness, creating offspring. A small number of newborn individuals undergo mutation to ensure diversity of the population. In general, individuals who have the best genetics survive according to "survival of the fittest", and in the final generation they represent approximations of the optimal solution. GA have recently been applied to industrial problems, e.g., in ironmaking for optimizing parameters in blast furnace charging (Saxén et al. 2006), and for parametric and structural optimization of black-box models based on neural networks (Pettersson et al. 2007).

In this study, a classical algorithm, called the non-domination sorting genetic algorithm (NSGA-II) for multi-objective optimization (Srinivas and Deb 1994, Deb et al. 2006) was used. The initialized population is sorted based on non-domination into Pareto fronts and a crowding distance is calculated for each individual. Parents are selected from the population by using binary tournament selection based on the rank and crowding distance, and the selected population generates offspring from simulated binary crossover and polynomial mutation operators. The population with the current population and current offspring is sorted again based on non-domination and only the best individuals are selected for the next generation. Finally, the best solutions are found on the rank-1 Pareto front.

3. SYSTEM STUDIED

A mini-3D conical hopper with a conical insert is the objective of the study (figure 2). Three factors, namely, the insert slope angle (θ), the length (L) of the slope and the distance (H) from the lower part of the insert to the exit of hopper are the geometry parameters studied within the ranges reported in table 1. The ranges were selected to ensure the continuity of discharging process. To minimize the computational effort, five different levels of each of the variables were used for generating an orthogonal design plan of 25 experiments. Discharging of hoppers with the corresponding inserts was simulated by DEM (table 2).

Table 1. *Factors and levels used in orthogonal experimental design.*

Factors	Level 1	Level 2	Level 3*	Level 4	Level 5
Slope angle, θ (°)	60	57,5	55	52,5	50
Length of slope, L (mm)	50	45	40	35	30
Position of insert, H (mm)	34	32	29,6	28	26

The EDEM software (DEM Solutions 2010) was applied to simulate the segregation of (10,000-17,000) ternary size particles in the discharging process. In the simulations, the particles were first charged into the hopper with a random filling method and were allowed to settle under gravity.

After forming a stable bed (cf. figure 2) with an upper surface on a given vertical level, the exit at the bottom was rapidly opened and the particles started flowing out until the hopper was emptied. A virtual cylinder (cf. fig 2B) at the exit records the number of particles of different size at various moments, and this gives the momentary fractions of particles of fine (m_f), intermediate (m_i) and coarse (m_c) size in the outflow as functions of the discharged mass fraction, $M = m_{out}/ m_{tot}$, where m_{out} is the cumulative mass of discharged material and m_{tot} is total mass of particles in the simulation. The data of the 25 experiments were used to train feedforward neural networks with four input variables (θ, L, H and M), using one hidden layer with 3-10 hidden nodes, and two output variables, $m_f(M)$ and $m_i(M)$. Obviously, $m_c(M) = 1 - m_i(M) - m_f(M)$.

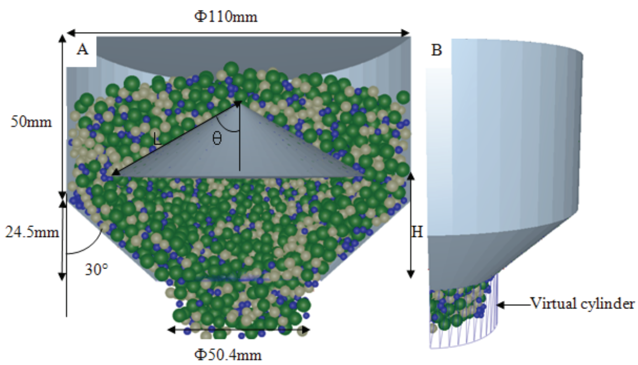

Fig. 2. *Hopper with coarse, intermediate and fine particles: (A) front view and (B) side view.*

Table 2. *DEM parameters used in the simulations.*

Parameter	Value
Particles	
Diameter 1 (mm)	2
Diameter 2 (mm)	3
Diameter 3 (mm)	4
Density (kg/m^3)	2285
Shear modulus (Pa)	10^7
Poisson's ratio	0.25
Coeff. of interparticle static friction	0.5
Coeff. of interparticle rolling friction	0.05
Coeff. of interparticle restitution	0.7
Plexi glass	
Density (kg/m^3)	1500
Shear modulus (Pa)	$2.2 \cdot 10^7$
Poisson's ratio	0.25
Coeff. of wall-particle static friction	0.5
Coeff. of wall-particle rolling friction	0.25
Coeff. of wall-particle restitution	0.2
Time step (s)	$4 \cdot 10^{-5}$

The multi-objective optimization algorithm NSGA-II was applied to determine input values for the three first inputs to the trained network, using a run with 21 uniformly distributed values for the discharge mass fraction, $M = 0, 0.05, 0.10,\ldots,1.0$. In the algorithm, a population size of 100 was used in 30 generations, with crossover and mutation probabilities of 90% and 10%, respectively. The two goals were to minimize the deviation in the mass fractions from $m_f = 0.0808$ and $m_i = 0.2727$, which correspond to the overall mass fraction of the two particle sizes in the whole batch.

4. RESULTS

Some results of the 25 experiments are illustrated in figure 3. Experiments 5-8 are seen to result in rather uniform discharge fractions of fine particles while the intermediate fraction shows some fluctuations, in particular for Experiment 6 where a final increase is observed. Similar findings apply to Experiments 13-16, with the difference that a strong final increase in the fine faction is observed for Experiment 13. An overall observation of the whole data set is that all experiments show segregation and that the particles in Experiments 8-20 exhibit serious segregation at the end of process. For instance, in Experiment 21 (not shown) there are only intermediate particles in the final mass to discharge from the hopper.

Before training the ANNs on the data, the inputs were normalized to yield a better numerical conditioning of the problem, and the data set was divided into a training, a validation and a test set. Problems were caused by large spikes in the output variables that occasionally occurred (e.g., for m_f in Experiment 13, figure 3). In order to prevent the networks from focusing on such extreme values, which would deteriorate the overall fit on the rest of the points, the data was filtered by

$$\tilde{m}_k = \min(\overline{m}_k + 3s_k, \max(m_k, \overline{m}_k - 3s_k)),$$

where $\overline{m}_k$ and s_k are the mean value and standard deviations, and k = f, i. Training was performed by the Levenberg-Marquardt method until the validation errors started to increase, and the correctness of the measure to stop training was visually confirmed by noting the performance on the test set. In order to guarantee the quality of the final solution, 100 initial weight sets were used for training the networks of each size. Visual inspection of the best fits revealed that the networks generally needed more than five hidden nodes to provide a good solution, and a network with seven hidden nodes was finally selected: figure 4 illustrates the filtered target outputs (dotted lines) and the fit (solid lines) of this network.

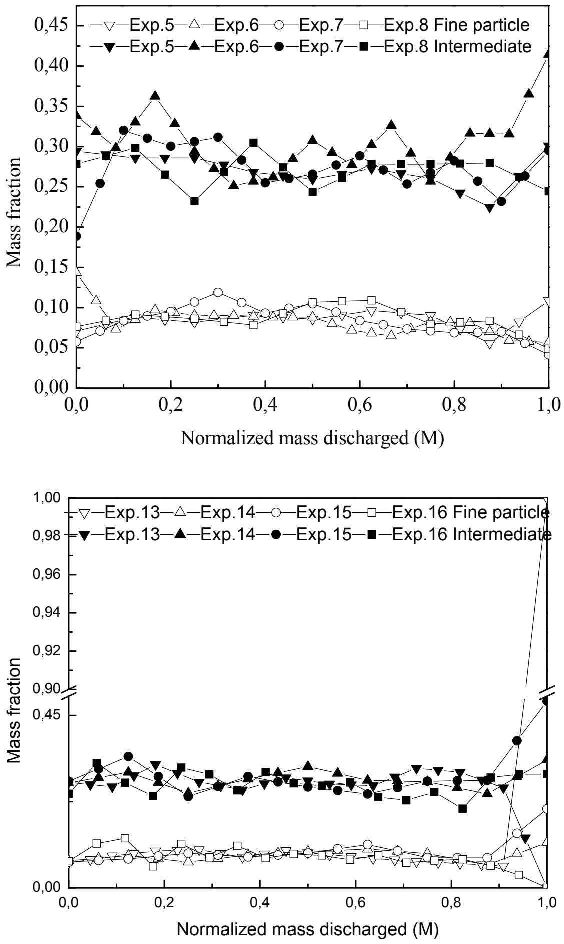

Fig. 3. Size segregation in hopper discharging process in some of the 25 experiments

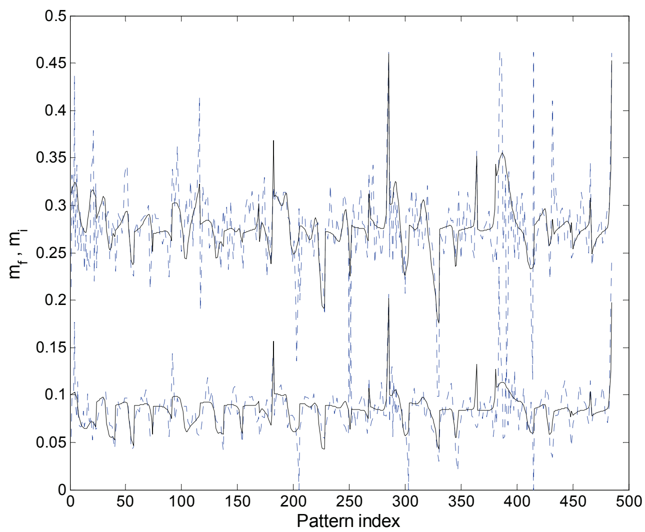

Fig. 4. Target outputs (dotted lines) for m_f (lower curves) and m_i (upper curves) and the corresponding approximations (solid lines) by a network with seven hidden nodes.

With this network, the NSGA-II algorithm was executed to yield solutions corresponding to low deviations of the mass fractions m_f and m_i from their overall mass fraction among all particles. The two goals were found to be partly conflicting, yielding Pareto frontiers with compromise solutions. For the purpose of illustration, we here select only one of the evolved solutions, which corresponds to the parameters $\theta = 56.7°$, $L = 32.4$ mm and $H = 33.0$ mm. In order to verify the results, these insert parameters were used in a DEM simulation. Figure 5 shows a comparison of the two outflow material fractions predicted by the neural model (solid markers) and by DEM (open markers). It is clear that the design has resulted in a discharging process where fine and intermediate particle fractions show only small fluctuations. Despite some discrepancy at the end of the discharging process, the approximated distributions are considered to be in overall agreement with the ones simulated by DEM.

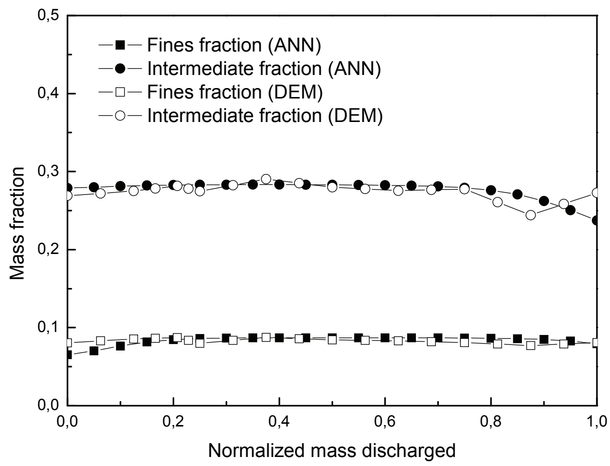

Fig. 5. Comparison of mass fractions predicted by the approximate model (solid markers) and predictions by the DEM model (open markers) for $\theta = 56.7°$, $L = 32.4$ mm and $H = 33.0$ mm.

5. DISCUSSION

This work has proposed a procedure for using DEM in design and illustrated it by optimizing a conical insert in a hopper to minimize particle segregation during the discharging process. The insert parameters were position, shape and size. An uncorrelated plan of experiments was created and DEM simulations were run. The results were approximated by a neural network, and the arising black-box model was used for finding minimum segregation conditions by optimizing the insert parameters by a multi-objective genetic algorithm. The study demonstrated that a proper design of an insert can reduce not only the funnel flow effect but also particle segregation. The methodology proposed is expected to be applicable to solving other complex design problems where the computational burden is considerable.

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REFERENCES

Chou, C., Lee, A., Yeh, C., 2009, Placement of a non-isosceles-triangle insert in an asymmetrical two-dimensional bin-hopper, *Adv. Powder Tech.*, 20 (1), 80-88.

Cleary, P.W., Sawley, M.L., 2002, DEM modelling of industrial granular flows: 3D case studies and the effect of particle shape on hopper discharge, *Appl. Math Mod.*, 26 (2), 89-111.

Cundall, P.A., Strack, O.D.L., 1979, A discrete numerical model for granular assemblies, *Geotech.*, 29 (1), 47-65.

Cybenko, G., 1989, Approximation by superposition of a sigmoid function, *Math Control, Signals Syst.*, 2 (4), 303-314.

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002, A fast and elitist multi-objective genetic algorithm: NSGA-II, *IEEE Trans. Evol. Comput.,* 6 (2), 182-197.

DEM Solutions, 2010, www.dem-solutions.com

Holland, J.H., 1975, *Adaptation in natural and artificial systems*, The University of Michigan Press, Ann Arbor, MI.

Johanson, J.R., 1967, The placement of inserts to correct flow in bins, *Powder Tech.*, 1 (6), 328-333.

Johanson, J.R., 1982, Controlling flow patterns in bins by use of an insert, *Bulk Solids Handl.* 2, 495-498.

Kaneko, Y., Shiojima, T., Horio, M., 1999, DEM simulation of fluidized beds for gas-phase olefin polymerization, *Chem. Eng. Sci.*, 54 (24), 5809-5821.

Ketterhagen, W.R., Curtis J.S., Wassgren, C.R., Hancock, B.C., 2008, Modeling granular segregation in flow from quasi-three-dimensional wedge-shaped hoppers, *Powder Tech.*, 179 (3), 126-143.

Ketterhagen, W.R., Curtis, J.S., Wassgren, C.R., Hancock, B.C., 2009, Predicting the flow mode from hoppers using the discrete element method, *Powder Tech.*, 195 (1), 1-10.

Li, Y., Xu, Y., Jiang, S., 2008, DEM simulations and experiments of pebble flow with mono-sized spheres, *Powder Tech.*, 193 (3), 312-318.

Nedderman, R.M., 1992, *Statics and Kinematics of Granular Materials*, Cambrige University Press.

Nguyen, V.D., Cogné, C., Guessasma, M., Bellenger, E., Fortin, J., 2009, Discrete modeling of granular flow with thermal transfer: Application to the discharge of silos, *Appl. Therm. Eng.*, 29 (8-9), 1846-1853.

Pettersson, F., Chakraborti, N., Saxén, H., 2007, A Genetic Algorithms Based Multiobjective Neural Net Applied to Noisy Blast Furnace Data, *Appl. Soft Comput.*, 7 (1), 387-397.

Saxén, H., Pettersson, F., 2006, Genetic evolution of novel charging programs in the blast furnace, *Trans. Indian Inst. Met.,* 59 (5), 593-605.

Srinivas, N., Deb, K., 1994, Optimization using nondominated sorting in genetic algorithms, *Evol. Comput.*, 2 (3), 221-248.

Stewart, R.L., Bridgwater, J., Zhou, Y.C., Yu, A.B., 2001, Simulated and measured flow of granules in a bladed mixer – a detailed comparison, *Chem. Eng. Sci.*, 56 (19), 5457-5471.

Tang, P., Puri, V.M., 2004, Methods for minimizing segregation: a review, *Part. Sci. Tech.*, 22, 321-337.

Yu, Y., Saxén, H., 2010, Experimental and DEM study of segregation of ternary size particles in a blast furnace top bunker model, *Chem. Eng. Sci.*, 65 (18), 5237-5250.

Zhou, C., Ooi, J.Y., 2009, Numerical investigation of progressive development of granular pile with spherical and non-spherical particles, *Mech. Mater.*, 41 (6), 707-714.

Zhu, H.P., Yu, A.B., 2005, Steady-state granular flow in a 3D cylindrical hopper with flat bottom: macroscopic analysis, *Granul. Matter*, 7, 97-107.

Zhou, Z.Y., Zhu, H.P., Yu, A.B., Wright, B., Zulli, P., 2008, Discrete particle simulation of gas–solid flow in a blast furnace, *Comput. Chem. Eng.*, 32 (8), 1760-1772.

OPTYMALIZACJA PROJEKTOWANIA ZSYPU METODĄ ALGORYTMÓW GENETYCZNYCH

Streszczenie

Zbiorniki różnego typu są często używane jako pośrednie magazyny przy przechowywaniu i transporcie materiałów sypkich. Podczas napełniania i opróżniania zbiorników może wystąpić zjawisko segregacji cząstek. Kształt zsypu ma wpływ na schemat wypływu cząstek ze zbiornika (przepływ masowy lub lejkowaty), a poszczególne elementy zsypu mogą wpływać na sposób segregacji cząstek. W pracy przeprowadzono badania stopnia segregacji w zsypie wykorzystując metodę elementów dyskretnych (ang. discrete element modeling – DEM). Ze względu na długie czasy obliczeń w tej metodzie, do prowadzenia obliczeń numerycznych zastosowano plan eksperymentu, w którym zmiennymi parametrami były kształt wstawki w zsypie oraz jej położenie. Uzyskane wyniki stanowią podstawę do opracowania modelu z wykorzystaniem sztucznej sieci neuronowej. Wykorzystując ten model przeprowadzono optymalizację kształtu wstawki metodą algorytmów genetycznych, przyjmując segregację jako funkcję celu. Najlepsze wyniki zostały następnie zweryfikowane metodą elementów dyskretnych. W konsekwencji zaproponowana metoda pozwala na rozwiązanie skomplikowanych problemów projektowania unikając znacznych nakładów obliczeniowych.

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