Development of a computational fluid dynamics model of an industrial scale dense medium drum separator

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\textbf{ABSTRACT}

The European Union is setting increasingly challenging targets for the waste recycling rates of its member states. This makes improvements in recycling processes, such as dense medium metal separation, a necessity. Dense medium metal separation takes place in a dense medium drum separator where the light metal floats and can be easily separated from more heavy metal, which will sink. Although dense medium separation has been applied in the coal and mineral mining industry for decades, prior research on modeling this process only focuses on first order models using measurement data of running installations. Such an approach, however, can not be applied to optimize the design of a separator. To overcome this drawback and to obtain new insights in the optimization of dense medium drums, a computational fluid dynamics based model is presented and validated in this paper. This model estimates the influence of these non-modelled effects on the separation efficiency in real industrial applications. Based on this study general guidelines are presented. Implementation of these to a separator resulted in an efficiency increase of roughly 5%, corresponding to an extra 2800 tons of aluminum separated each year.

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\section{1. Introduction}

A study, conducted by seven European Nations, showed that the circular economy could reduce greenhouse gas emissions by up to 70\%, increase the workforce by 4\% and drastically decrease the amount of waste produced (Stahel, 2016). Because of this immense potential, the European Union (EU) published the EU Action Plan for the Circular Economy, which comprises ambitious targets for the recycling rates that should be ambitioned by all member states. By 2030, the recycling rates for municipal and packaging waste are targeted to reach 65\% and 75\%, respectively (European Commission, 2015a). As potential energy and carbon dioxide savings were found particularly in the recycling of aluminum packaging waste, the proposed target rate for aluminum packaging is even higher and accounts to 85\% (European Commission, 2015b). Although recent recycling rates of 45\% and 67\% for municipal and packaging waste in the European Union are improving on a high level, further enhancement is necessary to meet the target values (Eurostat, 2016, 2018). Consequently, the state-of-the-art recycling processes have to be revised and optimized, including macroscopic studies investigating the material flow and general plant design, as well as more detailed analysis of key recycling processes.

The metal stream in a recycling plant passes through different processes, such as screening, magnetic separation, air separation, sink float separation and eddy-current separation, before it is melted and casted (Rousseau & Melin, 1989). In a first step, small objects are removed from the stream by screening and subsequently magnetic separation takes out the ferrous materials. Thereafter, the lightweight non-metals, such as plastic foils, foam or light wood are extracted from the stream by air separation in a zig-zag process. Next, the separation of all non-ferrous metals from the stream is conducted by eddy-current separation. From the separated non-ferrous fraction the different alloys are separated by multiple sink float separations, typically one 2.5 specific gravity-bath to remove the last heavy plastics and magnesium, as well as one 3.5 specific gravity-bath to remove heavier metals, for instance stainless steel, copper and zinc (Gaustad, Olivetti, & Kirchain, 2012).

Modern sink float separators are designed as Dense Medium Drums (DMDs). In Figure 1, the main flow direction and the working principle of DMDs are illustrated. The medium, usually a high density suspension...
of ferrous silicon or magnetite in water, enters the DMD through the main inlet and two side inlets. Most of the main inlet medium overflows on the float side. The surface flow in the separation zone, which is sequestered by the curtains, has the highest influence on the separation. In this part of the drum, the mixed material stream enters the drum by dropping the separation objects into the flow. When the medium density is controlled correctly, heavy materials sink while light ones float, as depicted in Figure 1. The main function of the side inlet flows is providing turbulent mixing to avoid sedimentation and to maintain the necessary surface level to allow objects to move out of the drum at the float side. Due to the rotation, spiral elements push objects which sank to the bottom towards the back of the drum. Here, sink lifters extract them through the sink side outlet.

DMDs may process pieces of 4–150 mm and are known for low operational costs and a high efficiency of 85–90% (Rousseau & Melin, 1989). However, these values strongly depend on the actual separator design and the application. Furthermore, DMDs are very effective in separating non-ferrous materials of hugely varying densities, such as materials from shredded automotive scrap (Gaustad et al., 2012). Other applications of sink float separation are the washing of coals from incombustible ashes, the separation of different minerals, in the mining industry, or of plastics in the recycling industry (Dodhiba, Haruki, Shibayama, Miyazaki, & Fujita, 2002; Meyer & Craig, 2010). The main reasons for separation inefficiencies in DMDs applied in the aluminum recycling industry are: (1) object-object interaction of arbitrarily shaped objects (e.g., bars, plates, cables, engine parts etc.), for instance sinking plates dragging smaller light objects with them, (2) objects with cavities where medium or air may get trapped, altering its effective density and (3) inhomogeneous medium density distribution caused by sedimentation effects in low speed areas of the DMD.

Since DMDs were first applied in the coal and mineral industries, most research in this field resides in these areas. Generally, a separation curve is measured or predicted, which connects objects with a specific density or terminal velocity to separation numbers. The first approaches to mathematically model DMDs used measurement data to tune first-order models often consisting out of only a few parameters (Baguley & Napier-Munn, 1996; Napier-Munn, 1991). More recent studies focus on developing dynamic models to control and predict the performance of specific machines (Meyer & Craig, 2015) or the whole process chain in a plant (King, 1999; Meyer & Craig, 2010). So far, only few studies focused on DMDs in recycling applications, applying either experimental (Dodhiba et al., 2002) or numerical methods (Eggers, Dewulf, Baelmans, & Vanierschot, 2017). However, the generic, simplified DMD geometries in these studies are only roughly comparable to state-of-the-art separators. Many effects which have been identified as primary reasons for misplacement, e.g., light objects reporting to the heavy side or heavy objects reporting to the light side, are not studied and the envisaged separators have never actually been run in industrial applications. Furthermore, the numerical results lack validation data.

To further accelerate the development of DMDs, a reliable model, predicting the effects of changes of the geometry and process parameters, is needed. Such a model can be applied during the (re)design phase of a DMD when changes are cheap and easy to implement. For this application, it is on the one hand crucial that the complex physical effects leading to separation inefficiencies described earlier are taken into account. On the other hand, it is important that the model remains computationally efficient to enable usage in industrial applications. Computational fluid dynamics (CFD) can simulate the flow field inside the drum, applying a combination of state-of-the-art modeling approaches at reasonable computational costs. Only based on the known physics of the flow field a prediction of its influence on the separation efficiency can be made.

CFD has been successfully used in different industrial processes such as separation cyclones (Saputro et al., 2018), heat exchangers (Ramezanizadeh, Nazari,
Ahmadi, & Chau, 2019) and others. Applying CFD to a DMD may be divided into four physical phenomena which need to be modeled and simulated. Firstly, a Reynolds Averaged Navier Stokes (RANS) approach models the turbulent flow field using an eddy viscosity (Menter, 1994). Secondly, the stream of medium and air is a two-phase flow with a free surface. In this study, a Volume of Fluid (VOF) method is implemented by using a passively advected scalar function which indicates the amount of medium at a specific point and time in the domain (Hirt & Nichols, 1981). This method has been applied to a variety of applications, for instance predictions of hydrodynamic coefficients (Eggers, Peeters, Slaets, & Vanierschot, 2019; Seo, Park, & Koo, 2017) or bubbly flows (Bolaños-Jiménez, Sevilla, Gutiérrez-Montes, Sanmiguel-Rojas, & Martínez-Bazín, 2011). Thirdly, the drum’s rotation influences the flow field and the separation efficiency. However, in most DMDs the rotations per minute are kept on a low level to prevent unpredictable movement of the material stream. Finally, the material stream is tracked through the flow field, using an Eulerian–Lagrangian model combining the continuous fluid phase with a Lagrangian solid phase. The method is a modified version of the Multi-phase Particle in Cell approach which is implemented in OpenFOAM and has been applied before to separation cyclones (Razmi, Soltani Goharrizi, & Mohebbi, 2019). The path of each separation object is predicted by summing up all forces acting on it and solving Newton’s equation of motion. Separation objects in DMDs applied in aluminum recycling differ in size between 4 and 125 mm and are often complexly shaped. Furthermore, up to 2,500,000 objects have to be tracked to generate reliable statistics about the object behaviour. For this application, models accurately resolving the object shape are too expensive and models which do not resolve the shape cannot handle objects of such large dimension. Therefore, a model which enables tracking of high numbers of large objects at the cost of stronger modeling assumptions, mainly no back coupling from the objects onto the flow and no density correction based on objects in a fluid cell, had to be developed. Hence, this study applies unresolved particle modeling but disables the re-coupling from the particles onto the flow to prevent non-physical behaviour in case of big objects in small Eulerian fluid cells (Eggers et al., 2017). As such, directly modeling effects being responsible for inefficiencies in DMDs are not possible. Hence, the simulation results have to interpreted within a modeling approach based on experiments, practical experience and theoretical boundaries. The key value in this model is the non-dimensional residence time (NDRT).

Although DMD separators are essential for efficient separation and purification processes in different fields, such as mineral, mining and recycling industries, state-of-the-art modeling is basic and major optimization potential was expected and found in this study. Hence, the aim of this research is to show that the proposed CFD-based method can model and optimize state-of-the-art, real size DMDs in industrial use. To achieve this, firstly, an industrial DMD was simulated leveraging CFD. Secondly, the DMD was examined experimentally to validate the numerical data. Thirdly, separation curves, which are commonly applied to separators in the mining and mineral industries, are predicted for the investigated separator. The results are validated against literature and the capabilities and limitations concerning the present case are discussed. Finally, the NDRT is proposed which adds additional, more detailed information on the process quality and may be extracted easily from the simulation. As such, it enables the process optimization by CFD simulations in DMDs.

2. Material and methods

2.1. Feed material

The feed of separation objects entering the drum consists out of a wide range of materials, including aluminum, stainless steel, copper, zinc, brass, printed circuit boards and not liberated combinations of materials, in different shapes, such as plates, crushed cans and cables, of length-scales between 4 mm and 150 mm. In comparison to classical DMD separation applications in the mining industry (Baguley & Napier-Munn, 1996) the variety in shape and size is high. This enables object-object interaction, for example sinking plates forcing smaller light objects with them, and sedimentation on separation objects, particularly in small cavities of highly folded light objects such as crushed aluminum cans, to become a major influence on the separation performance.

2.2. Fluid flow simulation

The open source software package OpenFoam (OpenCFD, 2018) solves the incompressible, isothermal RANS equations using a commonly applied finite volume method (FVM):

\[
\frac{\partial \bar{u}_i}{\partial x_i} = 0, \quad (1)
\]

\[
\frac{\partial \bar{u}_i}{\partial t} + \bar{u}_j \frac{\partial \bar{u}_i}{\partial x_j} = - \frac{1}{\rho} \frac{\partial p}{\partial x_i} + \frac{\partial}{\partial x_j} \left( \frac{1}{\rho} \left( T_{ij} - \bar{u}_i \bar{u}_j \right) \right) + g_i, \quad (2)
\]
where $\bar{u}_i$ is the Reynolds averaged velocity, $x_j$ the spatial coordinate, $t$ the time, $\rho$ the density, $\overline{p}$ the Reynolds averaged pressure, $T_{ij}$ the viscous stress tensor, $\overline{u}_i u'_j$ the Reynolds stress tensor and $g_i$ the gravitational acceleration. As in this equation system the turbulent fluctuations are time averaged, a turbulence model has to be applied. The k-ω SST turbulence model predicts the influence of the turbulent fluctuations on the mean flow (Menter, 1994). In combination with scalable wall functions (Spalding, 1961) it offers high flexibility, with respect to the wall resolution, which is necessary in complexly shaped industrial applications. Furthermore, it holds statistical information on the turbulence which is used to model the turbulence object interaction.

The two-phase system, air and dense medium, is modeled by the standard VOF approach implemented in OpenFoam (Ubbink, 1997). A scalar function $\phi$ describes the fraction of the different phases, e.g. air and a higher density fluid such as water or a suspension. $\phi = 1$ indicates the presence of the heavier medium, i.e. water or medium, $\phi = 0$ the presence of air and $0 < \phi < 1$ the free surface, a moving density discontinuity due to the different fluids. This scalar function is governed by the equation of passive advection:

$$\frac{\partial \phi}{\partial t} + \bar{u}_i \frac{\partial \phi}{\partial x_j} = 0. \tag{3}$$

Based on the scalar function, the local physical flow properties can be computed:

$$\rho = \phi \rho_{med} + (1 - \phi) \rho_{air}, \tag{4}$$

where $\rho_{med}$ is the medium density and $\rho_{air}$ the air density,

$$\mu = \phi \mu_{med} + (1 - \phi) \mu_{air}, \tag{5}$$

where $\mu_{med}$ is the medium viscosity, $\mu_{air}$ the air viscosity and $\mu$ is the mixture viscosity.

### 2.3. Separation object modelling

To track separation objects, the drag and the effective buoyancy force are summed up:

$$\frac{dv_j}{dt} = \frac{1}{m_p} (F_{B,j} + F_{D,j}), \tag{6}$$

where $v_j$ is the velocity of the separation object, $m_p$ its mass, $F_B$ the net buoyancy force and $F_D$ the drag force. Firstly, the net buoyancy force may be computed straightforward from the density ratio between medium and separation objects:

$$F_{B,j} = -\rho_p \cdot V_p \cdot v_i \cdot \left( 1 - \frac{\rho}{\rho_p} \right), \tag{7}$$

where $\rho_p$ is the object density and $V_p$ its volume. Secondly, the drag coefficient of a sphere models the drag force on the separation objects:

$$F_{D,j} = -\frac{1}{2} \cdot C_D(Re_p) \cdot |u_{r,j}| \cdot u_{r,j} \cdot A_p, \tag{8}$$

where $u_{r,j}$ refers to the relative velocity between the object and the local flow field, $A_p$ to its projected surface. $Re_p$ is the object Reynolds number:

$$Re_p = \frac{|u_{r,j}| \cdot d_p \mu}{\mu}, \tag{9}$$

where $d_p$ is the characteristic length of the object. The drag coefficient of a sphere may be estimated as:

$$C_D(Re) = \begin{cases} 0.424 & \text{if } Re \geq 1000 \\ 24(1 + 0.15 \cdot Re^{0.678}) & \text{otherwise} \end{cases}. \tag{10}$$

Different correlations for the prediction of the drag force are possible. However, in this study the sphere drag is applied to not further increase the already high computational costs.

Additionally, the turbulent fluctuations of the flow impose a randomly directed drag force on the separation objects. This, among the specific sink collector design and the drop off point of the separation objects, has been identified as one of the main reasons for displacement in DMDs in the coal industry (Baguley & Napier-Munn, 1996) and, hence, cannot be neglected. Although, the turbulent fluctuations are not simulated, turbulence models contain statistical information, the turbulent kinetic energy and the turbulent dissipation, which may be used to model the influence on the separation objects’ movement. In this study, eddy interaction modeling (EIM) is applied to incorporate these influences (Gosman & Ioannides, 1983). Before the drag force in Equation (8) is computed an additional turbulent component of the relative velocity is calculated and added to the mean relative velocity:

$$u_{r,j} = u_{mean,r,j} + u_{turb,r,j}, \tag{11}$$

where $u_{mean,r,j}$ refers to the mean relative velocity and $u_{turb,r,j}$ to the fluctuating one.

Based on the turbulent kinetic energy the fluctuation velocity’s magnitude may be estimated as:

$$|u_{turb,i}| = \sqrt{\frac{2k}{3}} \cdot \text{Gauss}(0, 1), \tag{12}$$

where $k$ is the turbulent kinetic energy and Gauss(0,1) a normal distribution with mean value of zero and a
variance of one. As the turbulence model assumes homogeneous turbulence, the fluctuation velocity’s direction is assumed to be randomly orientated:

$$\text{dir}_{\text{turb},i} = \begin{bmatrix} \text{rand}() \\ \text{rand}() \\ \text{rand}() \end{bmatrix} \quad \text{with} \quad |\text{dir}_{\text{turb},i}| = 1.$$  \hspace{1cm} (13)

In usual applications of unresolved Lagrangian models the influence from the solid phase onto the fluid phase is taken into account by source terms in the Eulerian fluid momentum equations. However, the separation objects in a DMD are often of bigger dimension than the Eulerian fluid cells, leading to a mesh to particle size ratio smaller one. As such, a source term-based modeling leads to non-physical results. To enable the modeling of a high amount of separation objects, which is necessary to achieve reliable statistical data, the back coupling from the solid phase into the fluid momentum equations and the density correction due to objects in fluid cells was disabled completely (Eggers et al., 2017). On the one hand, this seems to be a too strong assumption for the modeling of the detailed physics in the DMD. On the other hand, the objects are small in comparison to the geometry and the relevant flow features. Hence, their influence onto the flow field is considered to be small. Furthermore, the produced data could optimize an industrial DMD application.

2.4. Process assessment

2.4.1. Separation curves
Separation curves are a state-of-the-art measure to describe the efficiency of DMDs at different working points. These curves can either be measured directly or predicted by first-order models (Baguley & Napier-Munn, 1996) and more complex CFD simulations (Eggers et al., 2017). A separation number, the percentage of material reporting to the heavy side, is plotted over a density ratio or a terminal velocity of the separation objects. As such the performance of the drum can be described. The separation curves generated in this study are generated by assuming that any object touching the spiral or the drum wall is reporting to the heavy side. Objects leaving the drum with the flow through the light side are assumed to report to the light side.

2.4.2. Non-dimensional residence time
Figure 2 shows the quantities of a typical DMD geometry that influence the separation efficiency. Integrating along the path of a separation object yields the path length:

$$L = \int_C dS,$$  \hspace{1cm} (14)

where $dS$ is the integration variable following the path $C$. As the time averaged flow field is steady the average of the object velocity in the $x_1$ direction can be computed:

$$v_{m,1} = \frac{1}{L} \int_C v_1(x_i) \, dS.$$  \hspace{1cm} (15)

The velocity in the $x_3$ direction will be called terminal velocity and the averaged velocity in the $x_1$ direction main velocity. The length and height may be used together with the terminal and the main velocity to calculate the heavies’ sinking time and the floats’ residence time:

$$t_{\text{sink}} = \frac{SH}{v_3},$$  \hspace{1cm} (16)

$$t_{\text{float}} = \frac{SL}{v_{m,1}},$$  \hspace{1cm} (17)

where $SL$ and $SH$ are the separation length and height as described in Figure 2.

The determination of the terminal velocity of particles has been subject to plenty of research. Due to the directed movement, it may be estimated in a straight forward modeling approach computing a force balance between gravity and drag resistance, incorporating the particles’ shape with correction factors (Concha & Almen-dra, 1979; Heywood, 1962):

$$v_3 = \frac{\delta^2}{4d^2} \left( 1 + \frac{4d^{1.5} \sqrt{\frac{\rho}{C_0 \rho_0}}}{4d^{1.5} \sqrt{\frac{\rho}{C_0 \rho_0}}} \right)^{0.5} - 1 \right)^{-1} \sqrt{g},$$  \hspace{1cm} (18)
where

\[ d^* = \frac{d}{\varphi} \]  \hspace{1cm} (19) \]

and

\[ p = \left( \frac{3\mu^2}{4\Delta\rho\rho_{med}g} \right)^{1/3}, \]  \hspace{1cm} (20) \]

\[ q = \left( \frac{4\Delta\rho g}{3\rho^2_{med}} \right)^{1/3}, \]  \hspace{1cm} (21) \]

where \( d \) is a characteristic object diameter, \( \Delta\rho \) the difference between mixture and object density and \( g \) the gravitational constant. \( C_0 \) and \( \delta_0 \) are shape depended coefficients which may be calculated by linear regression:

\[ \ln C_0 = -5.99k + 1.95, \]  \hspace{1cm} (22) \]

\[ \delta_0 = 9.97k + 2.94, \]  \hspace{1cm} (23) \]

where

\[ k = V \cdot d_A, \]  \hspace{1cm} (24) \]

with \( V \) the object volume and \( d_A \) its projected diameter.

Using the floats’ surface residence time and the heavies’ sinking time the NDRT can be computed:

\[ t^* = \frac{t_{float}}{t_{sink}}, \]  \hspace{1cm} (25) \]

If a relevant number of floating separation objects is simulated their residence times may be used in Equation (25) to calculate an NDRT for every object. By visualizing the fractions of objects with a certain residence time in a bar graph an NDRT distribution, for a specific geometry in a specific working point, arises. As not all objects are dropped at exactly the same location, the drop off zone has a small length and width, and due to the stochastic turbulence dispersion force acting on the objects, the NDRT profile is non-homogeneous. In this study, the NDRT is the main optimization criterion which is used to assess the separation process. NDRT distributions may be used to assess the performance of the DMD. If \( t_{min}^* < 1 \) the heavy objects have no time to sink and will get miss placed due to over floating together with the floating objects. Therefore, \( t_{min}^* > 1 \) is a necessary condition for an efficient separation. An upper limit for \( t^* \) can not be derived directly. On the one hand, \( t^* \gg 1 \) gives the separation process time, minimizing the danger of inefficiencies due to over floating heavy objects. On the other hand, it corresponds to a high floats’ surface residence time which enables influences, such as object-object interaction, turbulence object interaction, sedimentation or accumulation of medium in cavities of separation objects. These can introduce inefficiencies due to light objects sinking and leaving the drum on the heavy side. Furthermore, high floats’ surface residence times slow the process down as light objects stay longer in the DMD. Hence, the possible material feed rate is lower. Therefore, the optimal NDRT has to be greater than one and depends highly on the specific process parameters, such as object size and shape distribution and the targeted material feed rate. However, once determined experimentally for a certain feed rate, shape and size distribution, it may be used to find the optimal geometry and mass flow by numerical simulations.

Several process parameters influence the NDRT. Firstly, a straight forward parameter is the non-dimensional drop off point:

\[ L^* = \frac{L_x}{L}, \]  \hspace{1cm} (26) \]

where \( L \) is total length of the drum and \( L_x \) is the perpendicular distance between the heavy side and the center line of the material stream’s drop off area. An increase of the non-dimensional drop off point leads to a decrease of the NDRT, because the SL is decreased. As such the non-dimensional drop off point may be used to determine the lower limit of the NDRT. If the separation efficiency is measured for a series of non-dimensional drop off points, a point may be observed where the heavy objects lack time to sink the separation height. The corresponding NDRT of these heavy objects is the lower limit for the NDRT. Secondly, the density ratio between heavy objects and medium influences the NDRT:

\[ \phi_{heavy} = \frac{\rho_{heavy}}{\rho_{med}}, \]  \hspace{1cm} (27) \]

where \( \rho_{heavy} \) is the heavy object density. If the ratio is increased, e.g. by decreasing the medium density, the heavy objects will sink faster and the NDRT drops. However, to secure the correct separation of light objects a certain density ratio between light objects and medium is necessary:

\[ \phi_{light} = \frac{\rho_{med}}{\rho_{light}}, \]  \hspace{1cm} (28) \]

where \( \rho_{light} \) is the light object density. This density ratio needs to be \( \phi_{light} > 1 \) as light objects would sink otherwise. To secure a reliable and efficient process a security factor has to be introduced as objects may become subject to different influences which are difficult to predict. In this process a ratio of at least \( \phi_{light} > 1.15 \) has been found to be necessary. However, this value depends highly on the DMD design and the material stream. Finally, the main flow rate is an important process parameter, altering the NDRT. Generally, an increase in mass flow is expected
Figure 3. Convergence of the mean NDRT value over time and tracked objects.

to decrease the NDRT, due to an increased main velocity. However, flow systems are highly non-linear and have to be investigated by either a simulation or an experiment.

2.5. Simulation strategy

A major challenge in CFD simulations is to determine when a sufficiently converged state is reached and the results of the simulation may be interpreted. In this study the heavy medium’s overall conversation of mass was used as convergence criterion. After reaching this criterion, the flow field was averaged for another 10 s to cope with transient effect inside the DMD. Subsequently, the flow field was in a time averaged converged steady state. As such it could be frozen during the object tracking simulations enabling fast and efficient simulations.

Based on the frozen flow field the path of the separation objects through the drum can be integrated and their residence times predicted. The convergence of the mean NDRT for the medium mass flow is shown in Figure 3. Objects are introduced at a constant rate, starting to leave the drum after roughly 5 s. Hence, the mean NDRT rises as more objects with higher NDRTs are leaving the drum. After a few seconds and 2,500,000 objects the mean NDRT value starts to stabilize and converges, while an increasing number of objects is tracked through the drum. As soon as the rate of change drops under a certain threshold the object tracking simulation is assumed to be converged.

2.6. Experiment

Validating numerical results on a full scale DMD in industrial use holds plenty of challenges. Due to the drum’s immense dimensions and its connection to the remaining material stream, the inner drum is not easily and safely accessible. This makes the installation and utilization of measurement devices often very difficult or even impossible. Furthermore, an experimental investigation is always related to down times of the DMD in the industrial process. Hence, experimental time is rare and drastically altering the installation is often not possible. Additionally, the medium and the DMD itself are not transparent making many experimental methods impossible to apply.

In this study the surface flow field inside the drum has been filmed, using a camera positioned in its upper part. In usual production the DMD runs using a suspension of ferrous silicon in water. Due to the DMD’s rotation and the suspension’s high viscosity, the lens of the camera becomes non-transparent after a few seconds. Running the drum without rotation to prevent this problem is not possible as the danger of heavy sedimentation and blockage in low speed areas is too high. Therefore, the experiments were conducted with pure water as medium. Nevertheless, even water becomes non-transparent in the DMD, due to its contamination with ferrous silicon powder. Furthermore, the flow rates into the drum could not be measured, as adding measurement devices to the piping system would have been a major interference with the industrial process. The drum was run at a high and a low mass flow, these values were compared to numerical results. Due to the limited amount of data extracted, this validation should be seen as a raw comparison between simulation and experiments, proving the applied state-of-the-art methods to capture the major effects occurring in the DMD.

2.7. Case setup

Figure 4 depicts the boundary conditions and the general case setup of the DMD simulation. Medium is fed into the drum through two side inlets, pointing left and right of the separation zone, and the main inlet, which provides the main flow in the DMD’s center. Medium may overfloat on the sinks’ and the floats’ side. Furthermore, separation objects are dropped into the stream from above the separation zone. The drop off location, the main inlet’s velocity and the medium density are parameters which will get varied to investigate their influence on the NDRT distribution. The physical properties and boundary conditions are described in full detail in Table 1.

2.8. Grid sensitivity analysis

The coarse mesh consists out of 18,817,960 cells while the fine one has 23,065,588 elements. The unstructured meshes consist mainly out of tetrahedrons in their
Figure 4. Case setup and boundary conditions of the simulation. The interior geometry is only sketched.

Table 1. Case setup and physical properties of the simulations.

|          | HMFa | HMFB | MMFC | LMFVD |
|----------|------|------|------|-------|
| $u_{\text{main}}$ (m/s) | 4.731 | 4.731 | 2.35  | 0     |
| $u_{\text{side}}$ (m/s)  | 2.535 | 2.535 | 1.258 | 2.535 |
| $\rho_{\text{med}}$ (kg/m³) | 3200  | 1000  | 3200  | 1000  |
| $\rho_p$ (kg/m³)          | 2700  | –     | 2700  | –     |
| $\mu_{\text{med}} \cdot 10^{-6}$ (m²/s) | 4.6875 | 1.004 | 4.6875 | 1.004 |

a High mass flow. b High mass flow validation. c Medium mass flow. d Low mass flow validation.

interior and prisms and pyramids handling the turbulent boundary layer in the vicinity of wall boundary conditions. The tetrahedrons are clustered in regions of interest including the spiral elements, which remove the sinking objects from the drum, the sequestered separation zone, the inflow tubing and the area in which the free surface is expected. The grid sensitivity may be evaluated by comparing relevant quantities, such as the mean NDRT or the maximum velocity in the separation zone’s surface flow, on different grids:

$$
\epsilon = \frac{P_1 - P_2}{P_1},
$$

(29)

where $P_1$ and $P_2$ refer to a quantities on the fine and the coarse grid, respectively. The velocity field in the drum shows good grid convergence, as the sensitivity of the maximum velocity in the separation zone has a low value of $\epsilon_{\text{velo}} = 1.7\%$, while the mean NDRT remains grid sensitive, $\epsilon_{\text{NDRT}} = 13.2\%$, due to it being integrated through the surface flow field in the separation zone. However, the for the process essential profiles remain similar in their general structure. Both feature a rather steep positive gradient at low NDRT values, leading to a maximum and a less steep negative gradient for higher NDRT values. Hence, the coarse grid is assessed to be sufficiently grid independent and is applied throughout this study.

3. Results and discussion

3.1. Validation

3.1.1. Flow validation

As stated in the methodology section the validation cases apply water as medium to allow visual access to the drum. Figure 5 a compares the simulated surface streamlines in the drum for the high (HMFB) and the low mass flow validation (LMFVD) case. In both flow situations the flow from the main and the side inlets surfaces in the separation zone. The location where the flow reaches the surface is called surfacing point. Here, the flow splits up into two directions, one heading towards the main inlet, slowly recirculating there, while the other one overflows at the drum’s float side. The side inlets’ stream introduces a small asymmetry in the flow field in the separation zone as it directly interacts with asymmetric spiral elements before going to the surface. The major part of the stream from the side inlets leaves the drum through the heavy side, never entering the separation zone. The slowly recirculating area close to the main inlet introduces small and even negative values of $\nu_{\text{m}}$. The surfacing point in the separation zone moves closer to the main inlet as the main flow increases. Hence, the size of the recirculation zone at the main inlet is reduced and the flow velocity increases.

The same configuration is visualized in Figure 5(b), showing the surface flow field filmed with a camera inside the drum. The flow is entering the drum through the main and the side inlets and overflows at the float side.
3.1.2. Separation validation

In Figure 6 predicted separation curves of the investigated DMD are depicted. Despite of the strong modeling assumptions, such as one way coupling between the Lagrangian and the Eulerian phases and spherical separation objects, the influences of the main process parameters, objects to medium density ratio and object diameters, could be predicted in accordance to literature. An increase of the density ratio introduces more sinking objects and objects of larger diameter lead to sharper separation curves (Baguley & Napier-Munn, 1996; Eggers et al., 2017). Furthermore, the produced NDRT profiles in this study were used to improve the real industrial process. Based on these curves aluminum, density ratio $\phi_{alu} = 0.84$, and stainless steel, $\phi_{ss} = 2.25$, are separated without misplacement. However, this is opposed by experience and measurements of the actual industrial process, where particularly aluminum reporting to the sink outlet may be observed. Two main factors, (1) sedimentation of ferro-silicon on separation objects and (2) complex object-object interaction, which cannot be simulated efficiently within an industrial application, cause this discrepancy. Hence, separation curves based on unresolved particle tracking heavily underestimate the influence of long residence times and are of limited use in recycling applications. As the produced separation curves give no meaningful results for the investigated material feed, they will not be analyzed within the parameter study. The only criterion capable to effectively assess the process quality in DMDs in complex recycling processes is the NDRT.

3.2. Parameter study

3.2.1. Drop off location

Figure 7 shows the NDRT distribution at the HMF working point based on simulation data. In the initial set
Figure 7. Non-dimensional residence time distribution for $L_x = 0.76$ (a), $L_x = 0.80$ (b), $L_x = 0.85$ (c) and $L_x = 0.90$ (d).

up of $L_x = 0.76$ the majority, roughly 90%, of the separation objects leave the drum after an NDRT between $t^* = 5$ and 9. These objects are the first group leaving the drum, being dropped close to the float side and on the sides of the separation zone. The objects being dropped in the center of the separation zone experience the highest velocities close to the drop off zone. However, these objects get slowed down and are eventually overtaken by the objects on the sides of the separation zone, as a recirculation zone in the center of the drum reduces the velocities. Although, the first group objects’ NDRT is the lowest of all in this set up, still $t^* \gg 1$. Hence, these objects have a risk of being misplaced due to stochastic influences, such as turbulent fluctuations, object-object interaction and sedimentation. The rest of the objects leave the drum in a linearly decaying number over a time range from $t^* = 9$ to $t^* = 29$, after the first group of objects left the drum. These are mainly objects dropping in medium or high distance to the float side in the center of the separation zone. Their NDRT is determined by (i) the exact acceleration they experience close to the drop off zone, (ii) the slow down in the recirculation zone in the drum and (iii) the actual distance they have to cover until they reach the floating side. Even though this group is small, the high NDRT introduces a high risk of misplacement.

By moving the drop off zone further downstream the whole profile gets shifted towards lower NDRT values, keeping essentially the same profile shape including a high number of low NDRT objects and a linear decay of the objects with increasing NDRTs. As such the drop off location offers a straightforward tool to influence the NDRT in a controllable and predictable way without having to introduce changes to the geometry.

3.2.2. Mass flow

Figure 7 depicts the NDRT for four different drop off locations at the medium mass flow (MMF) and the high mass flow (HMF). As expected the NDRT increases in case of a lower mass flow due to lower main velocities. Furthermore, the recirculation zone in the center of the drum increases drastically, slowing down more objects reducing their NDRT. As such, less objects, roughly 68% at $L_x = 0.76$, leave the DMD in the first group and the amount of objects in the linear decay zone increases. By further moving the drop off location at a lower mass flow, the objects are no longer subject to the acceleration at the initial drop off location. Hence, their NDRT is determined only by the amount of deceleration in the recirculation zone in the drum and the distance to the float side where they are dropped. Therefore, the profile becomes more homogeneous, spreading over the whole range of NDRTs.

Increasing the mass flow reduces the absolute NDRT and the range of NDRTs among the objects, leading to a higher object concentration at lower NDRTs. As it is favorable to generate a clearly defined NDRT for every object, this increases the process quality. However,
strong turbulent fluctuations and the high power consumption for industrial heavy medium pumps limit the mass flow.

3.2.3. Medium density

A straightforward approach to influence the NDRT is to alter the medium density. By decreasing the medium density the terminal object velocity and the NDRT decrease as well. Although altering the medium density influences the complete flow field, this study assumes that the influence is minor as long as one phase is much heavier than the other one. Comparing the validation cases with the separation cases supports this assumption. The investigated DMD runs with a density ratio between the light and the heavy medium of \( \phi_{\text{light}} = 1.185 \) while the experience-based minimum value is \( \phi_{\text{light,min}} = 1.15 \). Hence, the density medium is decreased until the minimum density ratio is reached. The change in medium density introduces an offset in the NDRT distribution. As long as the minimum density ratio between light and the medium, which may change with the geometry and the material stream, is not violated, this parameter offers and easy and reliable possibility to influence the NDRT profile directly.

3.2.4. Industrial separation process optimization

The DMD geometry investigated in this study had an NDRT profile which still held possibilities for optimization. A minimum NDRT of \( t_{\text{min}}^* = 5 \) and maximum of \( t_{\text{max}}^* = 29 \) was found in initial setup in Figure 7. This means sinking separation objects will have five to twenty-nine times more time to sink the SH then needed based on their modeled terminal velocity. On the one hand, this ensures a high purity on the heavy side as all objects have enough time to sink. On the other hand, it exposes floating separation objects, i.e. aluminum, at least five times longer to turbulence, sedimentation and object-object interaction, than theoretically needed, potentially introducing misplacement. Hence, a reduction of the NDRT values was expected to improve the separation efficiency. Based on the parameter study this could be achieved by (i) increasing the mass flow, (ii) decreasing the medium density or (iii) by decreasing the separation length. As the medium density could not be altered sufficiently without reducing the density ratio between light objects and medium too much and the mass flow was close to the pump’s maximum, decreasing the separation length by changing the drop off location was chosen as main measure to reduce the NDRT. The parameter study indicated that moving the drop off point further downstream would linearly decrease the NDRT of most of the separation objects. As such, the separation efficiency of the investigated industrial DMD was expected to be increased drastically. This trend could be proven in measurements during the running industrial process, as due to the optimization the amount of misplaced floating materials decreased by roughly 5% corresponding to an extra 2800 tons of aluminum separated each year. Hence, reducing the amount of misplaced floats holds considerable economical potential. It increases the purity of the heavy fraction and, more importantly, the light fraction output.

4. Conclusion

Although DMDs have been widely investigated in the mining industry, modeling approaches are still limited to first-order models heavily relying on measurement data as input. However, the enormous potential energy savings due to recycling and the strict regulations from the European Union make further improvements of recycling processes inevitable. Hence, this study applied advanced CFD methods to a full scale industrial DMD, for the first time. This does not only give major insights into flow phenomena occurring in existing DMDs, but also enables the use of CFD simulations during the design phase of next generation DMDs.

Furthermore, the application case holds additional challenges. Metallic objects in the recycling industry often have heavily folded, complex shapes. These are difficult to model, enable changes in effective densities of objects and complex object-object interaction. Thus, separation curves based on unresolved particle tracking, as in the mineral industry, cannot be applied to optimize DMD separators in the recycling industry. In this study the non-dimensional residence time is introduced to achieve an optimization criterion which can be easily extracted from the simulation yet holds a maximum information about the separation process. In the parameter study the influence of main flow rate, material drop off location and medium density are simulated and discussed. Recommendations are given how these parameters may be altered to reduce misplacement and improve the separation efficiency. By optimizing the non-dimensional residence time the misplacement in a industrial size state of the art separator could be reduced significantly. The process was improved yielding a higher recycling rate and considerable economical benefits. Hence, the method presented in this paper has been proven to be able to optimize full scale industrial dense medium drum separators.

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**Disclosure statement**

No potential conflict of interest was reported by the authors.

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