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A soft-sensor approach to mixing rate determination in powder mixers

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ABSTRACT

Mixing of powders is of great importance in food, chemical and pharmaceutical industries. However, direct online measurement of mixing is impractical due to difficulties in real-time particle sampling. In such systems, soft-sensors placed external to the equipment may be used to indirectly determine the behaviour of the system using relationships between internal and external phenomena. In this paper, a soft-sensor approach is studied for a ribbon powder mixer with 0, 2, 4 and 6 impeller spokes, and 20, 30, 40 and 50% volumetric particle filling, using two types of particles of different densities and a fixed impeller speed of 100 RPM. The particle data are based on DEM simulation results in a previous study. Force sensors along the underside of the mixer identify the number of particle-wall contacts and the force experienced by the sensors during the DEM simulations. This information is used along with mixing data to determine a relationship between external force data and internal mixing behaviour. The dividing rectangles global optimisation technique is used to approximate the mixing rate coefficient from particle data, and principal component analysis is used to develop a fast and practical means to estimate the mixing rate coefficient using only readings from external force sensors. This approach is then extended to allow for real time estimation of the required mixing time.

1. Introduction

Particle mixing is an important process in many food, chemical and pharmaceutical production lines. Well mixed ingredients are key to product reliability and reproducibility in these applications. In pharmaceutical applications, for example, mixing is commonly used to ensure that active ingredients are evenly distributed for controlled release and correct dosage, and to give tablets an even appearance [1]. Since an excessive or insufficient dose of a pharmaceutical could have severe health consequences, thorough particle mixing is crucial [1]. This mixing may by conducted as a continuous process, such as in many food production applications, or as a batch process [2, 3, 4]. Batch mixers are commonly found in particle mixing for pharmaceutical goods, where they are more suited to the regulations placed upon the manufacture of such goods [5]. One of the most commonly used batch mixers is the ribbon mixer, which is able to exert strong shear stresses upon the particles and effectively generate mixing by axial and rotational movement of particles [2].

Experimental and numerical methods are used to study ribbon mixers. An experimental study of mixing behaviour in a ribbon mixer has shown that the nature of the supporting spokes on the impeller affects the mixing rate, and the effect of the spokes varies with fill level [6]. Muzzio et al. [6] used a core sampler to collect samples of the mixture at several locations in the mixer, and studied the composition using near-infrared spectrometry (NIR) using relative standard deviation (RSD) as a measure of mixing. They showed that, for a 3-spoke blade, mixing was faster at low fill levels. However, for a 5-spoke blade, the high fill level achieved better mixing in the long run. Additionally, mixing performance can be poorer as observed when the blade rotation speed is fast enough for particles to be forced onto the walls where little mixing occurs [6]. A much more effective regime is avalanching, which can occur at lower blade rotation speeds and improves mixing performance. Avalanching is a major phenomenon at low fill levels, whereas it becomes very minor for large fill levels [6]. Low fill levels tend to experience more surface mixing compared to high fill levels, especially if the avalanching particles interact with the impeller shaft. Fill level is of great interest in particle mixing due to the throughput maximisation problem that arises by balancing the short mixing time and small volumes of low fill levels with the long mixing time and large volume of high fill levels [6]. DEM Simulation studies by Halidan et al. [3, 2] focus on the effect of cohesiveness in particles when being mixed in ribbon mixers. Their work showed that cohesiveness, characterised by the Bond number, decreased the rate of mixing. At high bond numbers, the limit of the final mixing was drastically reduced and the particles could not be well mixed with the conditions studied [2]. They showed that mixing was fastest for intermediate impeller speeds (100 RPM), where avalanching was dominant. At lower speeds the effect of avalanching was too small to achieve fast mixing, and at higher speeds the particles were forced into the wall where mixing is poor [3]. The particle scale mixing was compared to a macroscopic mixing index, and the disagreement in the data showed that the

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Nomenclature

$C_{\gamma,\epsilon}(t)$	Number of p-w contacts at time t for sensor γ in simulation ϵ
D	Dimension of the hyperrectangle for DIRECT method. Equal to the number of parameters
$E\{\cdot\}$	Expectation function
E^*	Young's Modulus ($kg\cdot m^{-1}\cdot s^{-2}$)
$F_{\gamma,\epsilon}(t)$	Sensor force data for sensor γ in simulation ϵ ($kg\cdot m\cdot s^{-2}$)
$\mathbf{F}_{c,ij}$	Elastic contact force between particles i and j ($kg\cdot m\cdot s^{-2}$)
$\mathbf{F}_{d,ij}$	Damped contact force between particles i and j ($kg\cdot m\cdot s^{-2}$)
I_i	Inertia of particle i ($kg\cdot m^2$)
L	Lipschitz constant: Upper bound of gradient of $\tilde{Q}$
$M(t)$	Lacey mixing index
$\mathbf{M}_{ij}$	Torque applied to particle i due to rolling friction with particle j ($kg\cdot m^2\cdot s^{-2}$)
$\hat{M}$	Fitted mixing index
N	Total number of sample volumes
P_l	Matrix containing the first l columns of V
Q	Objective function for DIRECT method
$\tilde{Q}$	Dimensionless objective function for DIRECT method
$\underline{\tilde{Q}}$	Lower bound of $\tilde{Q}$
R_i	Radius of particle i (m)
R_j	Radius of particle j (m)
R^*	Reciprocal of sum of reciprocals of radii R_i and R_j (m)
R^2	Coefficient of determination for linear regression
$\mathbf{R}_{ij}$	Vector from centre of particle i to contact point with particle j (m)
S	Singular value matrix
S_0^2	Variance of fully segregated state
S_R^2	Variance of fully mixed state
$S_t^2(t)$	Variance of local particle fraction
U	Unitary output matrix for singular value decomposition
V	Unitary input matrix for singular value decomposition
W	Matrix used for linear regression
X	Matrix of input vectors from all simulations
$X_{Testing}$	Matrix containing input vectors from all testing simulations
$X_{Training}$	Matrix containing input vectors from all training simulations
$X_i(t)$	Coordination number in sample i
$\mathbf{X}_\epsilon$	Input vector for PCA from simulation ϵ
Z	Standard normal distribution
$Z_{Testing}$	Standardised matrix containing input vectors from all testing simulations
$Z_{Training}$	Standardised matrix containing input vectors from all training simulations
$\mathbf{Z}_\epsilon$	Standardised input vector for PCA from simulation ϵ
$\mathbf{b}$	Regression coefficients
c_n	Normal damping coefficient
c_t	Tangential damping coefficient
d_ξ	Distance from centre to vertex of rectangle ξ
e	Euler's number
$\mathbf{e}$	Error vector from least squares regression
f_n	Magnitude of the normal contact force ($kg\cdot m\cdot s^{-2}$)
$\mathbf{g}$	Gravitational acceleration ($m\cdot s^{-2}$)
i	Counter variable
j	Counter variable
k	Mixing rate constant as determined by DIRECT approach (s^{-1})
$\tilde{k}$	Dimensionless mixing rate constant as determined by DIRECT approach
$\tilde{k}_{min}$	Value of $\tilde{k}$ that minimises $\tilde{Q}$
$\hat{k}_\epsilon$	Mixing rate coefficient for simulation ϵ determined by PCA method (s^{-1})
$\mathbf{k}_{Training}$	Vector of mixing rate coefficients for training simulations determined by DIRECT method
$\hat{\mathbf{k}}_{Training}$	Vector of mixing rate coefficients for training simulations determined by PCA method
l	Number of principle components being used in reduced order PCA model
l_i	Number of particles that make contact with particle i
m	Number of input values for each simulation in PCA
m_i	Mass of particle i (kg)
m_j	Mass of particle j (kg)
m^*	Reciprocal of sum of reciprocals of masses m_i and m_j (kg)
$\hat{\mathbf{n}}$	Unit vector in normal direction
p	True particle fraction throughout the mixture
p_i	Proportion of particle A in sample i
$s_{y_\epsilon}{}^2$	Sample variance of y_ϵ
t	Time (s)
t_0	Initial time (s)
t_f	Time at which particles are considered to be well mixed (s)
$\hat{t}_f$	Time at which particles are considered to be well mixed (s)
v_i	Velocity vector of particle i ($m\cdot s^{-1}$)
v_{ij}	Relative velocity vector of particle j with respect to particle i ($m\cdot s^{-1}$)
w_T	Sum of all w_i
$w_i(t)$	Weighting factor
x	Example original variable for PCA
$x_{b,\beta,\gamma,\epsilon}$	Number of forces in bin β for sensor γ in simulation ϵ
$x_{c,\gamma,\epsilon}$	Number of p-w contacts per unit time for sensor γ in simulation ϵ
$\bar{x}$	Mean of each feature in the training data set
$\bar{x}_{\gamma,\epsilon}$	Arithmetic mean of sensor force data for sensor γ in simulation ϵ ($kg\cdot m\cdot s^{-2}$)
y_ϵ	Orthogonal variables based on original variables x
Σ_x	Covariance matrix
α_i	Coefficient vector for linear transformation
α_j	Coefficient vector for linear transformation
α_ϵ	Coefficient vector for linear transformation
β	Bin number that force data is grouped into
γ	Sensor number
δ_n	Normal displacement (m)
δ_t	Tangential displacement during contact (m)
$\delta_{t,max}$	Maximum tangential displacement during contact (m)
ϵ	Counter variable for simulation number
ε	Mean-square error
ζ	Counter variable for all potentially optimal rectangles
η	Rotation speed (RPM)
λ_ϵ	The ϵ^{th} eigenvalue of Σ_x
μ_r	Rolling friction coefficient
μ_s	Sliding friction coefficient
ξ	Counter variable
ρ_A	Density of particle A ($kg\cdot m^{-3}$)
ρ_B	Density of particle B ($kg\cdot m^{-3}$)
σ	Standard deviation of $X_{Training}$
$\hat{\sigma}$	Poisson's Ratio
τ	Time delay (s)