

Performance evaluation of a rotational barrel segment for low-density polyethylene masterbatch dilution in single-screw extrusion: Microscopy-based distributive and dispersive indices with process trade-offs

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ABSTRACT

Mixing quality in polymer extrusion is critical when additives are incorporated through masterbatches. This work evaluates a patented rotational barrel segment (RBS) in a single-screw extruder, separately quantifying distributive and dispersive mixing and relating them to process trade-offs. RBS rotational speed and direction, barrel/die temperature, and a downstream Cut Rings section were investigated during dilution of a blue masterbatch in LDPE. From optical micrographs (50× and 100×, three locations), an image-analysis workflow provided a distributive index (DMI) and a dispersive index (DsMI), interpreted with the measured process variables. Counter-rotation improves distributive mixing and gives the highest mixing score (MixScore = 61.6 at Nb = −50 rpm vs. 57.9 neutral), at the cost of specific energy (3443.9 vs. 2590.9 kJ/kg). Strong co-rotation gives the best dispersive performance with the highest throughput and low specific energy (Nb = +50 rpm: DsMI = 52.7, Q = 6.54 kg/h, E_{total} = 2482.6 kJ/kg). Raising temperature from 170 to 190 °C lowers pressure and energy but degrades distributive mixing. The Cut Rings section is beneficial only in an intermediate co-rotating case. The RBS therefore acts as an effective mixing variable.

Keywords: polymer extrusion, rotational barrel segment, dispersive mixing, distributive mixing, microscopy-based image analysis.

INTRODUCTION

Polymer extrusion is widely used to incorporate additives such as pigments, stabilizers, fillers, and functional agents into polymer matrices. In industrial practice, these additives are often introduced as masterbatches, which must be diluted efficiently during extrusion. This creates two simultaneous mixing requirements: the additive must be distributed uniformly at the macroscopic scale to avoid streaks and shading variations, and it must be dispersed at the microscopic scale to reduce agglomerates that cause specks and local property defects [1–4].

These two requirements correspond to different physical mechanisms. Distributive mixing is associated with spatial rearrangement, stretching, splitting, and recombination of material elements, whereas dispersive mixing is associated with the breakup of agglomerates under sufficient hydrodynamic stress [3–5]. Because these mechanisms may respond differently to screw geometry, barrel kinematics, temperature, and throughput, mixing performance should not be evaluated using a single qualitative indicator. Instead, distributive and dispersive effects should be quantified separately and then interpreted together with process variables

such as pressure, melt temperature, power consumption, and output [6–9].

From a process-development standpoint, a persistent challenge is that mixing is often assessed using indirect indicators (e.g., visual inspection, color variation, filter performance), which can obscure the mechanism underlying poor quality and complicate optimization. This motivates microstructure-based metrics that are sensitive to additive distribution and agglomerate size, and that can be related to measurable process signals such as power draw, pressure profile, melt temperature, and output. At the same time, extrusion is a continuous process, and the time history experienced by material elements, summarized by the residence-time distribution (RTD), is fundamental to interpreting mixing outcomes [10, 11]. Modern RTD studies now extend beyond global outlet curves and increasingly resolve local RTD behavior inside extruder elements through advanced modeling, highlighting the role of flow topology and transport barriers in mixing [12, 13]. In addition, recent work on online optical monitoring supports the practical value of measurement strategies that connect mixing quality to real-time process signals [14].

In this work, we consider the mixing of a polyolefin matrix with a blue masterbatch in an extrusion configuration that includes a rotational barrel segment (RBS) positioned downstream of the melting and compression zones. The RBS introduces an additional controllable kinematic degree of freedom: its rotation speed and direction can be adjusted independently of the screw. In counter-rotation (RBS rotating opposite to the screw), the relative surface velocity in the barrel region increases, which may promote stronger local deformation; in co-rotation, the relative velocity decreases, and the flow may become more conveying-dominated. In both cases, the modified velocity field can affect distributive renewal, dispersive stress histories, pressure build-up, melt temperature, and throughput [3, 4].

The present work investigates a RBS integrated into a single-screw extrusion system. Unlike passive screw-tip mixers, the RBS introduces an additional controllable kinematic variable: the barrel segment can rotate independently of the screw, either in co-rotation or counter-rotation. This changes the relative motion between the screw, the rotating sleeve, and the polymer melt, potentially affecting deformation history,

residence time, pressure build-up, melt temperature, and mixing quality [3, 4].

The RBS studied here corresponds to geometry C from previous technical and CFD-based developments of this active plasticizing concept [15, 16]. Therefore, the novelty of the present paper lies not in the proposal of the RBS concept itself, but in its experimental evaluation under masterbatch dilution conditions, using microscopy-based indices to distinguish between distributive and dispersive mixing and to relate them to extrusion process trade-offs. In contrast with the earlier RBS studies [15, 16], which were conceptual or CFD-based and did not report experimental mixing morphology, the present work provides (i) experimental data under realistic masterbatch dilution, (ii) a separate quantification of distributive and dispersive mixing from micrographs, and (iii) an explicit linkage of both indices to measured process variables (pressure, melt temperature, specific energy, and output).

To address these needs and evaluate experimentally a previously proposed RBS configuration under masterbatch-dilution conditions, we apply a structured methodology that quantifies distributive and dispersive mixing separately using microscopy image analysis at two magnifications (50× and 100×), with images acquired at multiple sampling locations for each operating condition. This distinguishes the present work from earlier CFD-based RBS evaluations, which focused on numerical comparison of candidate geometries using flow-based mixing indicators rather than experimental masterbatch-dilution assessment [15].

The main objective of this work is to experimentally quantify the effects of RBS speed, rotation direction, temperature level, screw–RBS relative motion, and downstream mixing geometry on masterbatch mixing in single-screw extrusion. Mixing is assessed using optical microscopy and image analysis, from which two complementary indices are obtained: a distributive mixing index based on spatial uniformity of detected pigment features, and a dispersive mixing index based on the particle-size tail.

The specific goals are: (i) to compare counter-rotation, neutral rotation, and co-rotation of the RBS; (ii) to evaluate whether increasing the barrel/die temperature improves or degrades distributive and dispersive mixing; (iii) to examine the role of screw–RBS relative motion; (iv) to compare the RBS-only configuration with a

downstream Cut Rings mixing section; and (v) to interpret mixing improvements together with energy demand, pressure, melt temperature, and output [7, 17].

The contribution of this work is an experimental and process-oriented assessment of an active RBS mixing concept. The study shows how RBS kinematics can shift the balance between distributive uniformity and dispersive agglomerate control, and demonstrates that the best operating condition depends on the targeted defect mechanism and on acceptable energy/output constraints. In this sense, the paper provides a practical framework for evaluating active mixing devices using microscopy-derived metrics coupled with extrusion operating data.

In addition, this work provides three specific contributions compared with previous studies on the rotating barrel segment concept. First, it presents an experimental evaluation of the RBS under realistic masterbatch dilution conditions in a single screw extruder, whereas earlier works were predominantly conceptual or numerical (CFD-based). Second, it introduces a structured methodology for quantitative mixing assessment based on microscopy that separates distributive and dispersive effects using two complementary indices – DMI and DsMI – computed consistently across all operating conditions. Third, it links the obtained mixing quality indices to key extrusion process variables, such as specific energy input, pressure, melt temperature, and throughput, enabling the analysis of trade-offs between mixing performance and energy and production requirements.

STATE OF THE ART

Mixing mechanisms and mixing devices in extrusion

Mixing is a defining capability of extrusion-based polymer processing, yet it remains one of its most difficult functions to design and evaluate quantitatively. Because polymer melts flow under highly viscous, laminar conditions, the absence of turbulence means that homogenization relies on kinematics (stretching, folding, reorientation, splitting, and recombination) and on stress-driven breakup mechanisms, all of which are strongly coupled to viscosity and temperature [3, 4]. Masterbatch dilution places this challenge in a

particularly strict form: the process must eliminate macroscopic concentration non-uniformity (streaking) while simultaneously suppressing the tail of the agglomerate size distribution (specks), and both outcomes can be sensitive to processing conditions and melt rheology [1, 2].

In single-screw extrusion, mixing is usually improved by modifying screw geometry, adding mixing sections near the screw tip, or adjusting operating conditions such as screw speed, temperature profile, and throughput [3–5]. These strategies influence the deformation history imposed on the melt and therefore affect distributive and dispersive mixing in different ways.

Active barrel concepts offer an alternative approach by modifying the boundary motion of the flow. A rotating barrel segment introduces an additional kinematic input that can be adjusted independently of screw speed. However, such active concepts must be assessed not only by mixing quality, but also by their effects on pressure generation, melt temperature, power consumption, and throughput [7, 17, 18].

A foundational theoretical perspective for understanding why geometry matters is the kinematic view of laminar mixing, in which stretching and folding can generate rapid homogenization by increasing interfacial area and reducing segregation length scales [19]. Distributive mixing depends strongly on repeated splitting/recombination and cross-sectional renewal, whereas dispersive mixing depends on achieving stresses sufficient to overcome the cohesive strength of agglomerates [3, 5]. Recent research has strengthened this viewpoint by explicitly identifying mixing barriers and transport structures in extruder elements using flow-topology tools, indicating that local regions of poor transport can limit mixing even when average shear rates appear favorable [13].

In parallel with device development, the field has advanced through quantitative mixing indices and multi-objective frameworks that formalize trade-offs. Domingues, Gaspar-Cunha, and Covas proposed global indices for distributive and dispersive mixing in extrusion, enabling systematic comparison of screw performance and operating conditions using consistent, computation-ready measures [6]. More broadly, extrusion design and operation are inherently multi-criterion problems, and recent reviews emphasize that optimization should jointly consider mixing, energy consumption, throughput, and thermal limits [7].

Decision-support approaches for polymer extrusion explicitly address these trade-offs and provide structured methods for selecting operating points from Pareto sets, rather than relying on a single mixing metric [17].

Quantitative evaluation of distributive and dispersive mixing

A second major topic concerns the measurement and quantification of mixing. Variance-based concepts (e.g., intensity and scale of segregation) provide classical foundations for distributive mixing assessment [20, 21]. Mixing evaluation in extrusion can be based on indirect process indicators, visual inspection, color uniformity, tracer response, residence-time distribution, or microstructural analysis [10, 11, 20, 21]. For masterbatch dilution, microscopy and image analysis are particularly useful because they allow direct observation of pigment-rich features and agglomerates. However, the choice of metric is critical. A mean particle size alone may not capture visible defects because large surviving agglomerates in the upper tail of the size distribution can dominate product quality [1, 3]. Similarly, particle-size statistics do not necessarily describe whether pigment features are spatially uniform across the extrudate.

For this reason, the present work separates distributive and dispersive assessment. Distributive mixing is evaluated from the spatial uniformity of detected features across the image field, while dispersive mixing is evaluated from tail-sensitive particle-size descriptors. This approach is suitable for comparing operating conditions because it distinguishes whether a process change improves spatial redistribution, agglomerate breakup, or both, while remaining consistent with broader efforts to quantify mixing using objective, computation-based descriptors [6, 8, 9, 22].

In practice, distributive mixing is often evaluated using concentration-uniformity proxies: colorimetry (CIELAB coordinates), image-based variance metrics, and tracer sampling strategies. These measures align with variance-based theory but require careful definition of scale and sampling, as they may not detect rare but critical large defects [20, 21]. Dispersive mixing is typically evaluated by measuring morphology or particle-size distribution using microscopy and image analysis. A recurring message in masterbatch-related literature is that tail-sensitive statistics are

often more relevant than the mean size, because the largest surviving agglomerates dominate the risk of visible defects [1, 3]. Recent comparative studies across melt mixers further support the need to evaluate dispersion and distribution separately, since different mixers can improve one while leaving the other unchanged [9]. Scale-up studies also show that dispersive mixing performance may not scale trivially with throughput or screw speed, underscoring the need for objective metrics and mechanistic interpretation [23].

Alongside offline morphology measurement, there is growing interest in online monitoring to support process control and reduce reliance on post-process microscopy. Optical monitoring has been demonstrated in co-rotating twin-screw extrusion to track mixing performance and detect changes in dispersion state, thereby enabling faster screening of operating conditions and screw configurations [14]. Although online signals typically require calibration against morphology or defect metrics, these approaches align well with industrial needs for rapid diagnosis and robust control.

Active barrel/RBS concepts and research gap

Previous work on rotating or active barrel concepts has shown that barrel kinematics can modify flow patterns and potentially improve mixing [16, 18]. In particular, earlier studies of the RBS concept, including CFD-based comparisons of alternative geometries, suggested that counter-rotation may improve calculated mixing performance [15]. Nevertheless, experimental evidence under realistic masterbatch dilution conditions remains limited. To the best of the authors' knowledge, no previous study has reported experimental mixing morphology obtained with an RBS operating during masterbatch dilution: the available RBS literature [15, 16, 18] is restricted to conceptual designs, technical descriptions, and CFD analyses. Likewise, studies of other mixing devices in single-screw extrusion typically report a single aggregate mixing response, without separating distributive and dispersive outcomes from the same experimental samples. Moreover, previous studies have not clearly separated distributive and dispersive outcomes while simultaneously considering process trade-offs such as energy consumption, pressure, melt temperature, and output.

This gap motivates the present study. In particular, previous experimental assessments of mixing in extrusion frequently relied on global color measurements or qualitative visual inspection, which provide a single aggregate response and cannot distinguish whether a poor result originates from non-uniform spatial distribution or from surviving agglomerates. The DMI/DsMI pair used here quantifies these two mechanisms separately, from the same micrographs, using objective and reproducible image-analysis criteria. By combining microscopy-based mixing indices with measured extrusion variables, the work provides an experimental assessment of whether the RBS can serve as an active process variable for tuning mixing performance.

CASE STUDY

Materials

The polymer matrix used in this study was low-density polyethylene (LDPE), commercial-grade Malen E FGAN 23-D003. This material is supplied in pellet form and is characterized by a density of 0.924 g/cm³ and a melt flow rate of 0.28 g/10 min (190 °C/2.16 kg). According to the supplier, this grade offers high impact resistance, good mechanical strength, and recommended processing temperatures of 170–220 °C, making it suitable for extrusion.

A blue masterbatch was used as the coloring additive to assess mixing quality. Its use provides clear optical contrast against the natural LDPE matrix, enabling the identification of pigment-rich features and poorly dispersed regions in microtomed sections. The masterbatch was added at 2 wt.% and used as a practical tracer for evaluating both the spatial distribution of detected features and the persistence of larger agglomerates in the extrudate. The masterbatch was a commercial blue concentrate supplied by Permedia Sp. z o.o. (Poland) based on a polyethylene carrier resin compatible with the LDPE matrix and containing approximately 35 wt.% of an organic blue pigment whose exact type is proprietary to the supplier. It was fed into virgin LDPE at 5.8 wt.% (0.145 kg of masterbatch per 2.5 kg batch), yielding a final pigment content of approximately 2 wt.%. Because the carrier is polyethylene-based, no compatibility issues with the LDPE matrix are expected, so the detected

features reflect mixing performance rather than thermodynamic incompatibility.

Although this tracer system is suitable for comparing the relative mixing performance of the tested configurations, a more demanding inorganic dispersion system, such as TiO₂ in the same LDPE matrix, is proposed as future work to further validate dispersive mixing performance.

Extruder setup and operating conditions

The experimental program was designed to evaluate four main effects (Table 1): (i) the influence of RBS rotational speed and direction at $N = 70$ rpm and 170 °C (runs A–H), (ii) the influence of barrel and die temperature level for selected RBS conditions at $N = 70$ rpm (runs J–N), (iii) the influence of RBS rotation at a reduced screw speed of $N = 50$ rpm, using neutral, co-rotating, and counter-rotating RBS conditions (runs T–X), and (iv) the influence of a downstream Cut Rings screw-tip mixer under selected RBS operating conditions (runs O–S). For the RBS-only configuration, the screw speed was set primarily to 70 rpm, while the RBS speed ranged from –50 to +50 rpm, with negative values indicating counter-rotation relative to the screw and positive values indicating co-rotation. Two temperature levels were considered for the barrel and die zones, namely 170 °C and 190 °C, while the feed-zone temperature was maintained at 20 °C.

A full factorial matrix was not adopted; instead, a matched-pair design was used, in which each effect is evaluated by comparing runs that differ only in the variable of interest. This reduces the number of runs to a practicable level while preserving direct comparability. Runs were not randomized, but each run was carried out only after 15 min of process stabilization, and the output was averaged over five samples, which mitigates systematic drift between conditions.

Additional tests were carried out at a reduced screw speed of 50 rpm to isolate the effect of RBS rotation at a different screw speed. These runs comprise a neutral RBS condition (T: $N = 50$ rpm, $N_b = 0$ rpm) and four rotating RBS conditions spanning counter- and co-rotation (U: $N_b = -30$ rpm; V: $N_b = -50$ rpm; W: $N_b = +30$ rpm; X: $N_b = +50$ rpm). This subset enables comparison between neutral, co-rotating, and counter-rotating RBS operation at the same screw speed. Direct residence-time-distribution measurements are outside the scope of the present study.

For the Cut Rings tip configuration, experiments were conducted at $N = 70$ rpm and 170°C , using selected N_b values matching those of the RBS-only cases: $N_b = 0, -30, -50, +30$, and $+50$ rpm. This allows direct comparison between the RBS-only configuration and the RBS plus Cut Rings configuration at equivalent screw speed, RBS speed, and temperature conditions. The complete matrix of operating conditions is summarized in Table 1.

The screw used in the experiments had a total length corresponding to $L/D = 24$ (600 mm), as shown in Table 2, which characterizes all the elements. The frontal part of the screw, namely sections L5 and L6, can be removed and replaced with a screw section with the geometric characteristics of section L5, but with a total length of $5 L/D$. Thus, in the experiments, we used two versions of the screw: i) the RBS plus the conventional downstream screw; and ii) the RBS plus downstream L5 and L6 (Cut Rings section). The screw pitch was square, that is, equal to the external screw diameter (25 mm). In the RBS region, the screw does not have flights

because the helical channel is provided by the rotating sleeve itself. This geometric arrangement ensures proper interaction between the screw and the RBS and is consistent with the operating principle of the active plasticizing system described in the underlying technical development (Figure 1).

To enhance mixing performance, two mixing configurations were considered. The first was a rotational barrel segment (RBS) located at the beginning of the metering zone, at approximately $L/D = 15$. In the present work, the RBS corresponds to the previously proposed geometry C, selected from a family of RBS concepts reported earlier. The device consists of a rotating sleeve manufactured from 38HMJ steel, with nitrided working surfaces, mounted on bearings that allow independent rotation relative to the screw, as represented in Figure 2. The active RBS section has a total length of $4.2 L/D$ (105 mm) within the processing zone. The inner surface of the sleeve component, with the same length, contains a helical channel with the same pitch as the screw flight, whereas the screw surface is

Table 1. Experimental runs performed (CRT – Cut Ring Tip)

ID	Mixing configuration	Operating conditions								
		N (rpm)	N_b (rpm)	T_s ($^\circ\text{C}$)	T_{b1} ($^\circ\text{C}$)	T_{b2} ($^\circ\text{C}$)	T_{b3} ($^\circ\text{C}$)	T_{d1} ($^\circ\text{C}$)	T_{d2} ($^\circ\text{C}$)	T_{d3} ($^\circ\text{C}$)
A	RBS	70	0	20	170	170	170	170	170	170
B	RBS	70	-10	20	170	170	170	170	170	170
C	RBS	70	-30	20	170	170	170	170	170	170
D	RBS	70	-50	20	170	170	170	170	170	170
F	RBS	70	10	20	170	170	170	170	170	170
G	RBS	70	30	20	170	170	170	170	170	170
H	RBS	70	50	20	170	170	170	170	170	170
J	RBS	70	0	20	190	190	190	190	190	190
K	RBS	70	-30	20	190	190	190	190	190	190
L	RBS	70	-50	20	190	190	190	190	190	190
M	RBS	70	30	20	190	190	190	190	190	190
N	RBS	70	50	20	190	190	190	190	190	190
T	RBS	50	0	20	170	170	170	170	170	170
U	RBS	50	-30	20	170	170	170	170	170	170
V	RBS	50	-50	20	170	170	170	170	170	170
W	RBS	50	30	20	170	170	170	170	170	170
X	RBS	50	50	20	170	170	170	170	170	170
O	RBS + CRT	70	0	20	170	170	170	170	170	170
P	RBS + CRT	70	-30	20	170	170	170	170	170	170
Q	RBS + CRT	70	-50	20	170	170	170	170	170	170
R	RBS + CRT	70	30	20	170	170	170	170	170	170
S	RBS + CRT	70	50	20	170	170	170	170	170	170

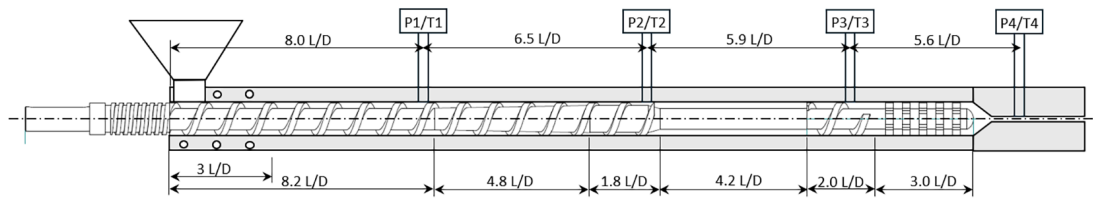


Figure 1. Geometry of the extruder used - RBS, plus downstream L5 and L6 (Cut Rings section)

smooth over the RBS region. Under these conditions, the conveying and deformation channel in that zone is formed by the rotating sleeve geometry rather than by the screw flight itself. This configuration allows the sleeve to rotate either in the same direction as the screw or in the opposite direction, thereby modifying the local kinematics of the polymer melt and, consequently, the mixing conditions.

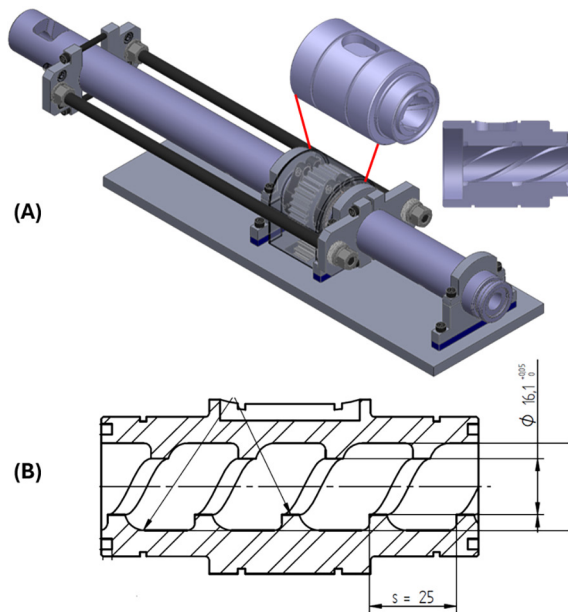


Figure 2. Geometry of the RBS:
(A) 3D representation of the extruder barrel and the RBS sleeve; (B) RBS technical drawing

The second mixing configuration employed a Cut Rings screw-tip mixer mounted at the end of the screw. Cut-ring tips are recognized as intensive screw-tip mixing elements used in single-screw extrusion and have been reported in comparative studies alongside other tip geometries, such as pineapple and Maddock tips. In the present study, this configuration was used to compare the effects of a conventional screw-tip mixing element and the RBS-based configuration under selected operating conditions.

Based on this experimental configuration, the following section describes the test procedure, sample preparation, microscopy-based characterization, and the quantitative metrics used to evaluate distributive and dispersive mixing.

Experimental procedure

Extruder sampling

For each experimental run listed in Table 1, the extruder was set up under the prescribed operating conditions and operated for 15 min to stabilize the process before data acquisition and sampling.

After stabilization, the following process variables were recorded: screw amperage, screw power consumption (P_w), RBS power consumption (P_{wRBS}), melt pressure at the barrel and die locations (P1–P4), melt temperature at the corresponding locations (T1–T4), and mass output. The mass output Q was calculated as the

Table 2. Screw geometry and configuration, as illustrated in Figure 1 (D_i – internal screw diameter)

Screw zones	Description	L (mm)	L/D	D_i (mm)
L1	Feed	205	8.2	16.8
L2	Compression	120	4.8	16.6–21.0
L3	Metering	45	1.8	21.0
L4	RBS	105	4.2	16.0
L5	Screw section	50	2	16.0
L6	Mixing section	75	3	16.0
Total		600	24	

average of five samples, each collected over 30 s. Finally, an extrudate was collected for posterior image analysis. For runs with neutral RBS rotation ($N_b = 0$), the RBS power contribution was considered zero because the barrel segment was not actively rotated.

From the measured process data, the following process indicators were calculated: (i) specific screw energy, $E_{\text{screw}} = P_w/Q$; (ii) total specific mechanical energy, $E_{\text{total}} = (P_w + P_{w\text{rbs}})/Q$; and (iii) a temperature-ratio indicator, T_4/T_{f1} , used as a simple measure of melt-temperature rise relative to the first die temperature measurement. Here, Q is the measured mass output. Residence-time-distribution measurements were not performed in the present study; therefore, residence-time effects are discussed only qualitatively, based on screw speed, output, and flow-rate changes.

After each run, an extrudate sample was collected for microscopy-based mixing analysis. Samples were sectioned from the transverse cross-section of the extruded profile using a Leitz 1401 microtome equipped with a glass knife, producing 10 μm thick sections. The sections were mounted on glass slides for bright-field transmission optical

microscopy. Images were acquired using a Leica DMP4 microscope equipped with a 0.55 $\times$ camera adapter and a Leica K3C digital camera, controlled through Leica Application Suite X (LAS X). For each run, images were collected at 50 $\times$ and 100 $\times$ magnification in three positions across the section: near both edges and at the center.

Microscopy image analysis

Mixing indices and particle-size distributions were obtained by applying the same image-analysis workflow to every micrograph from all experimental runs, including the added reduced screw-speed baseline T . Results were then aggregated by experiment ID, magnification (50 $\times$ and 100 $\times$), and sampling location. The procedure consists of four stages: (1) image preparation and scale calibration, (2) region-of-interest (ROI) definition, (3) particle/feature segmentation and sizing, and (4) calculation of distributive and dispersive mixing indices, followed by summary tables and histograms. A detailed step-by-step description of the Algorithm 1, including pseudocode and all parameter values, is provided in the Supplementary Material.

Pseudocode for Images Analysis

```

for each image
{
    read RGB image
    detect scale bar ->  $\Delta$  ( $\mu\text{m}/\text{pixel}$ )
    define ROI = image excluding bottom band
    grayscale ROI
    threshold = Otsu(grayscale central crop)
    mask = grayscale < threshold
    label connected components in mask
    for each component
    {
        measure area, bbox
        if area too small/large or bbox too elongated: reject
        else compute  $d_{\text{eq}}$  from area and  $\Delta$ 
    }
    compute DMI from particle centroids on 8 $\times$ 8 grid
    compute DsMI from D95 and Dmax of  $d_{\text{eq}}$ 
}
aggregate results by (experiment, magnification) across 3 locations:
{
    mean  $\pm$  SD of DMI and DsMI
    histograms (counts/ $\text{mm}^2$ ) for 50 $\times$  and 100 $\times$ 
}
    
```

Algorithm 1. Pseudocode for images analysis

All calculations were implemented in Python using standard scientific libraries for image processing and data analysis [24–28]. The same code was used for all experiments to ensure reproducibility.

1. Image preparation and scale calibration.

All micrographs were read as RGB images. Because particle sizing must be reported in micrometers (μm), each image was calibrated by estimating the pixel size, Δ ($\mu\text{m}/\text{pixel}$), from the embedded scale bar. The scale bar (a horizontal black segment near the bottom of the image) was detected automatically; the detection procedure is described in the Supplementary Material. The bar length in pixels, L_{px} , was then converted to the pixel size:

$$\Delta = \frac{L_{\mu\text{m}}}{L_{px}} \quad (1)$$

where: $L_{\mu\text{m}}$ is the scale bar length printed on the image. In this study, only two magnifications were used; therefore $L_{\mu\text{m}}$ was interpreted as 25 μm for 50 $\times$ and 10 μm for 100 $\times$. This step is critical because all reported particle diameters and all area-normalized counts depend on Δ .

2. Region of interest (ROI).

To avoid counting the scale bar and its label as particles, a bottom band of the image ($\approx 12\%$ of the image height) was excluded from the analysis. The remaining pixels define the ROI used for segmentation and particle counting. The analyzed physical area, A_{ROI} , was computed from the number of ROI pixels, N_{ROI} , using:

$$\begin{aligned} A_{ROI}(\mu\text{m}^2) &= N_{ROI} \Delta^2 \Rightarrow \\ A_{ROI}(\text{mm}^2) &= \frac{N_{ROI} \Delta^2}{10^6} \end{aligned} \quad (2)$$

This area is required to report particle number densities and histogram counts per unit area.

3. Segmentation of particles/features and particle sizing.

Within the ROI, pigment features were extracted using grayscale thresholding. The ROI was converted to grayscale, and a global threshold was computed using Otsu's method [29] applied to a central region of the image to reduce edge and annotation effects. Pixels darker than the threshold were classified as "features," producing a binary mask. Connected-component labeling was then used to define individual features (regions). Region measurements (e.g., area

and bounding box) were computed using standard labeled-region tools [24].

To reduce artifacts, each region was filtered using three criteria:

1. Minimum area: very small regions were removed to suppress noise.
2. Maximum area: extremely large regions (relative to the ROI) were discarded as illumination/background artifacts.
3. Aspect ratio: highly elongated regions were removed to reduce the counting of scratches or edge artifacts.

Each accepted region was treated as one particle/feature and converted to an equivalent circular diameter. If A_{px} is the region area in pixels, the physical area is $A = A_{px} \Delta^2$ (μm^2). The equivalent diameter is:

$$d_{eq} = 2 \sqrt{\frac{A}{\pi}} \quad (3)$$

This produces a set of particle diameters (μm) for each image. For each experiment and magnification, particle-size statistics were computed by pooling the particle diameters from the three locations (D50, D90, D95, and maximum diameter D_{max}).

4. Distributive and dispersive mixing indices.

Two indices were computed for each image and then combined across magnifications and sampling locations. Location-to-location variability is reported because it reflects the spatial variability of mixing along the extrudate. These three locations are within-run spatial replicates; independent repeated runs were not performed. Consequently, the reported SD quantifies spatial homogeneity within one run, and differences between conditions are interpreted as consistent trends supported by the process data rather than as formally tested statistical differences.

Distributive Mixing Index (DMI, 0–100)

Distributive mixing was evaluated from the spatial uniformity of particle distribution [4, 20]. The ROI was divided into an 8×8 grid. For each grid cell, the number of particles was counted using particle centroids. Let n_k be the count in cell k and $\bar{n}$ the mean count across the 64 cells. The coefficient of variation is:

$$CV = \frac{\sigma_n}{\bar{n}} \quad (4)$$

where: σ_n is the standard deviation of $\{n_k\}$. A perfectly uniform distribution gives low CV . The DMI for each image was defined as a bounded score:

$$DMI = \frac{100}{1 + CV} \quad (5)$$

Higher DMI indicates a more uniform particle distribution and therefore better distributive mixing.

Dispersive mixing index (DsMI, 0–100)

Dispersive mixing was evaluated from the particle-size distribution tail, because large surviving agglomerates are most relevant for speck defects [3, 4]. From the diameters measured in each image, two tail descriptors were computed: D_{95} (95th percentile) and D_{max} (maximum). These were mapped into bounded penalty scores:

$$I_{95} = \frac{100}{1 + \frac{D_{95}}{5}} \quad (6)$$

and

$$I_{max} = \frac{100}{1 + \frac{D_{max}}{10}} \quad (7)$$

and combined to form the dispersive index:

$$DsMI = \sqrt{I_{95} \cdot I_{max}} \quad (8)$$

With this definition, DsMI decreases when large particles are present (large D_{95} and/or D_{max}), and increases when the distribution tail shifts to smaller sizes.

Combination across magnifications and locations

Thus, DMI and DsMI were first obtained separately for each image at each magnification and location, and only afterwards combined into experiment-level indicators.

For each sampling location $i = 1, 2, 3$, the magnification-specific indices were combined as:

$$DMI_i = 0.7 \cdot DMI_{(50.i)} + 0.3 \cdot DMI_{(100.i)} \quad (9)$$

$$DsMI_i = 0.3 \cdot DsMI_{(50.i)} + 0.7 \cdot DsMI_{(100.i)} \quad (10)$$

The weighting scheme reflects the role of each magnification in the analysis. For distributive mixing, the 50× images were given higher weight because they cover a larger field of view and are therefore more representative of spatial uniformity across the section. For dispersive mixing, the 100× images were given greater weight because they offer higher sensitivity to smaller features and the upper tail of the particle-size distribution.

The scaling constants in Equations 6 and 7 (5 μm for D_{95} and 10 μm for D_{max}) are practical anchors chosen so that each penalty score equals 50 when the tail descriptor reaches a size at which agglomerates become visually critical in the extrudate; they act as fixed normalizations applied identically to all runs. A sensitivity check was performed across all 22 runs, in which the magnification weights in Equations 9 and 10 were varied over the range 0.6/0.4 to 0.8/0.2 (baseline 0.7/0.3). The best-performing condition for each index was unchanged (run T for DMI and MixScore; run H for DsMI, except at the two lowest weights, where H and N exchange first place with a baseline separation of only 0.10 points against reported standard deviations of 3.74 and 4.77), and the three highest-ranked runs for DMI ($T > D > B$) and for MixScore ($T > D > H$) were identical at every weight tested. Rank correlations with the baseline remained high (Spearman $\rho \geq 0.994$ for DMI, ≥ 0.964 for DsMI, ≥ 0.984 for MixScore), and every reordering that did occur involved runs separated by less than 2.1 points, i.e., well within the reported location-to-location scatter. The comparative conclusions of this work are therefore robust with respect to the choice of magnification weights. The filtering criteria (minimum area, maximum area fraction, and aspect-ratio limit) act identically on all images, so moderate variations of these thresholds shift all indices systematically without altering the relative ranking of the operating conditions.

For each experiment, the combined location-level values were then summarized as mean $\pm$ standard deviation across the three sampling locations:

$$DMI = \text{mean}(DMI_i), i = 1, 2, 3 \quad (11)$$

$$DsMI = \text{mean}(DsMI_i), i = 1, 2, 3 \quad (12)$$

For summary comparisons, an overall mixing score, MixScore, was calculated as the arithmetic mean of DMI and DsMI:

$$\text{MixScore} = \frac{DMI + DsMI}{2} \quad (13)$$

This combined score was used only as a practical ranking indicator. DMI and DsMI were always interpreted separately because distributive and dispersive mixing correspond to different physical mechanisms.

Histograms and particle number density

For each experiment, particle-size histograms were computed separately at 50× and 100×, using the same bin edges to ensure comparability. To compare absolute particle populations between images and magnifications, histogram counts were normalized by the analyzed area:

$$\text{counts/mm}^2 \text{ in bin } j = \frac{N_j}{\Sigma A_{ROI}} \quad (14)$$

where: N_j is the number of particles in the size bin j , and ΣA_{ROI} is the total analyzed area (mm^2) pooled across the three locations for that experiment and magnification.

Implementation and reproducibility (Python workflow)

All steps (scale detection, ROI cropping, Otsu thresholding, labeling, filtering, sizing, DMI/DsMI computation, and histogram generation) were automated using a Python script to ensure consistent processing across all experiments. The complete Python script, including all parameter values, is provided as Supplementary Material. The main filtering parameters were: Otsu threshold computed on the central crop of each grayscale image; minimum region area of 40 px; maximum region area of 2% of the ROI area (to reject merged blobs); and maximum aspect ratio of 12 (to reject scratches and elongated artifacts). Figure 3 illustrates the validation of these criteria by showing retained particles and rejected artifacts from two representative runs.

RESULTS AND DISCUSSION

Demonstrative example of the image-analysis workflow

Figure 3 illustrates how the microscopy images were processed to extract the particle population used in the distributive and dispersive mixing analysis. For each micrograph, the procedure identifies discrete pigment-rich

features that appear as darker regions in the image, rather than the continuous blue background coloration. In many cases, the masterbatch produces a relatively smooth blue tint over extended regions of the section; because this tint does not form separate connected components after thresholding, it is not counted as an individual particle. Instead, the analysis focuses on discrete detected features obtained after grayscale conversion, thresholding, connected-component labeling, and region filtering.

In Figure 3, green contours indicate accepted features and orange contours indicate rejected objects. The rejected objects correspond mainly to artifacts or unreliable detections for the particle-size statistics, such as highly elongated scratches, very small, noisy regions, or unusually large merged regions. This filtering step is particularly important for the dispersive mixing analysis because the dispersive mixing index (DsMI) is sensitive to the upper tail of the particle-size distribution and must therefore avoid non-particle artifacts that would artificially inflate the large-size tail.

Although the outlined areas may appear visually very different between experiments A and G, and although the accepted contours occupy only a limited fraction of the image area, the number of detected features remains sufficiently high to support statistically meaningful particle-size analysis. For experiment A, the total number of detected particles pooled across the three sampling locations was 7.782 at 50× and 2.678 at 100×. For experiment G, the corresponding totals were 2.841 at 50× and 1.464 at 100×. In the specific example images shown in Figure 3 (location 1), the algorithm detected 2.589 particles (50A1) and 654 particles (100A1) for experiment A, and 588 particles (50G1) and 317 particles (100G1) for experiment G. These counts show that the indices are calculated from hundreds to thousands of detected features per condition, which provides a sufficiently broad basis for comparing the particle-size distributions and the associated tail-sensitive dispersive metrics.

Figure 4 presents the corresponding particle-size distributions for the same two experiments, reported as number density (counts per mm^2 per size bin) as a function of equivalent particle diameter. The distributions are plotted separately for 50× and 100× because each magnification resolves a different size range and samples

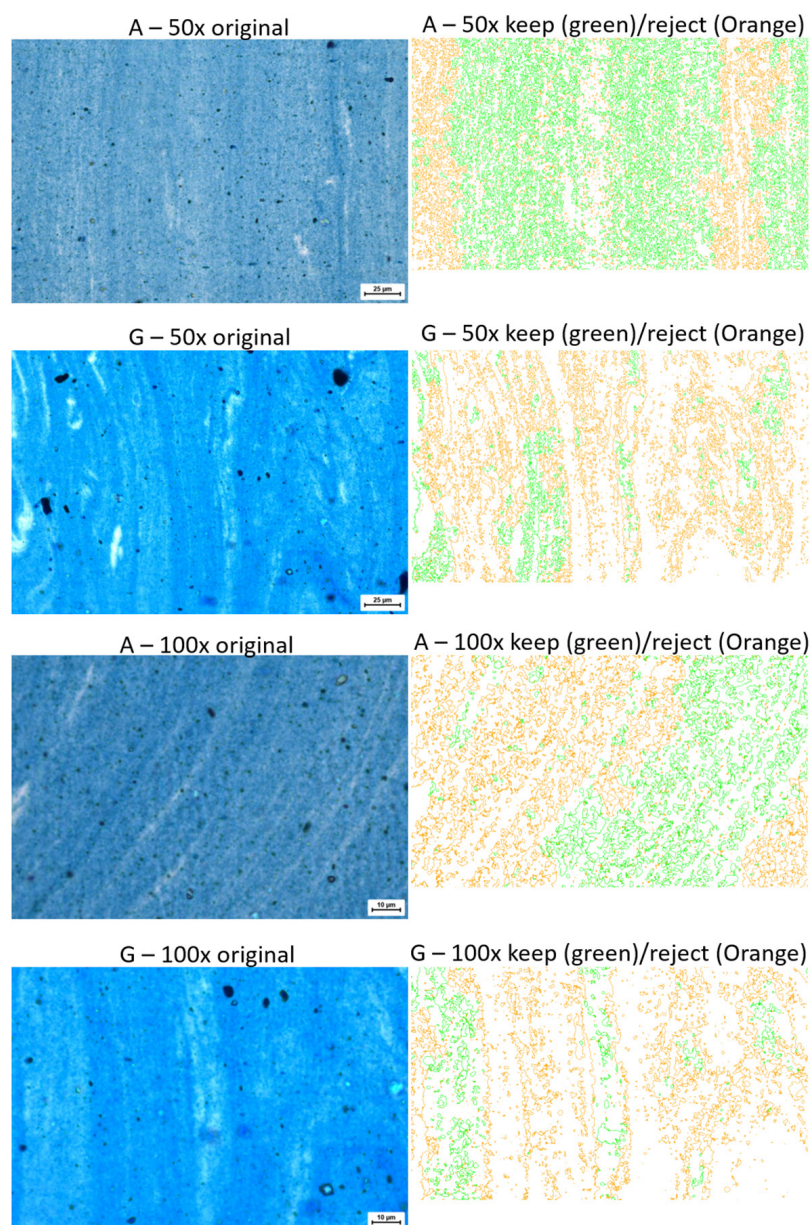


Figure 3. Example of particle detection for experiments A and G at 50× and 100×
 Green outlines: retained particles; orange outlines: rejected artifacts (e.g., scratches, noise, merged regions).
 The scale-bar band is excluded. Total particles across three locations: A = 7.453 (50×), 2.404 (100×);
 G = 2.707 (50×), 1.423 (100×)

a different physical area. For each magnification, particles from the three sampling locations were pooled, and the histogram counts were normalized by the analyzed ROI area, allowing direct comparison between conditions.

The histograms illustrate differences that are not always evident from visual inspection alone. In particular, the 100× images provide greater sensitivity to smaller features and the upper tail of the size distribution used in the calculation of DsMI, whereas the 50× images provide complementary information on coarser structures.

Thus, the example shown in Figures 3 and 4 demonstrates how the microscopy images are converted into quantitative information on feature size and spatial distribution.

Tables 3 and 4 summarize, respectively, the mixing indices and the main process variables for all experimental runs. These tables provide the quantitative basis for the discussion developed in the following subsections, where the effects of RBS speed and direction, temperature level, reduced screw speed, and the downstream Cut Rings mixing device are analyzed in detail.

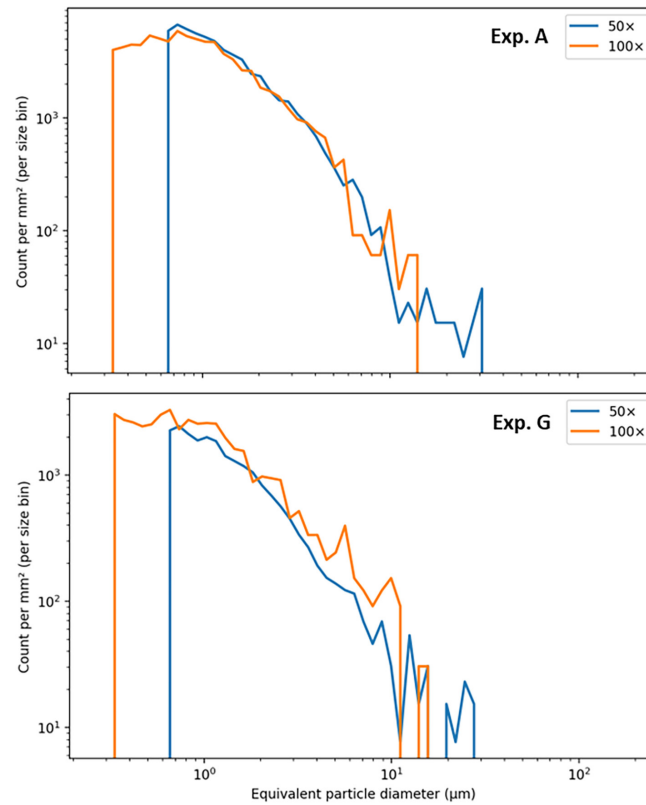


Figure 4. Particle-size distributions for experiments A and G at 50× and 100×, reported as counts per mm² per size bin (log–log). Counts were pooled across the three locations and normalized by the analyzed ROI area

Table 3. Mixing indices per run (50× and 100×). Values are mean ± SD across three locations (n = 3; 6 images/run)

Exp	DMI	STD_DMI	DsMI	STD_DsMI	MixScore	STD_MixScore
A	67.13	2.68	48.58	7.32	57.85	2.55
B	73.07	6.45	46.84	1.96	59.96	4.00
C	71.89	6.75	45.45	0.58	58.67	3.33
D	74.90	9.35	48.31	1.18	61.61	4.72
F	58.28	6.71	46.73	2.70	52.50	2.43
G	61.25	7.67	50.28	3.43	55.76	2.88
H	68.11	6.87	52.72	3.74	60.42	3.25
J	60.24	8.39	47.97	2.17	54.11	3.71
K	56.15	7.28	52.25	5.05	54.20	1.93
L	64.14	12.85	48.12	3.29	56.13	5.02
M	51.30	15.93	49.97	2.14	50.63	7.04
N	44.97	16.40	52.63	4.77	48.80	6.57
T	79.32	1.43	45.57	1.15	62.45	0.95
U	63.46	7.53	46.31	2.13	54.88	4.46
V	52.73	6.23	51.48	4.61	52.10	2.24
W	64.28	9.41	46.30	4.52	55.29	3.80
X	55.93	6.74	50.41	4.24	53.17	1.82
O	62.09	2.59	47.92	0.48	55.01	1.54
P	58.13	6.83	46.90	1.11	52.52	3.94
Q	64.54	2.44	44.49	2.04	54.51	0.43
R	66.61	5.49	50.81	6.69	58.71	5.03
S	65.61	4.60	47.99	4.74	56.80	0.49

Table 4. Process variables and trade-off metrics per run. Mixing performance (MixScore) is reported together with power, specific energy (Etotal), output (Q), and die-entry pressure/temperature (P4, T4, T4/Tf1)

ID	Pw (kW)	Pwrbs (kW)	Etotal (kJ/kg)	Q (kg/hr)	P4 (MPa)	T4 (°C)	T4/Tf1	MixScore
A	3.8	0.00	2590.9	5.280	21.45	169.5	0.997059	57.85
B	3.55	0.485	2882.1	5.040	21.65	168.6	0.992647	59.96
C	3.4	1.03	3069.3	5.196	21.00	169.0	0.994118	58.67
D	3.4	1.72	3443.9	5.352	21.40	169.2	0.995294	61.61
F	3.3	0.37	2463.1	5.364	21.70	168.0	0.988235	52.50
G	3.2	0.72	2523.6	5.592	22.40	169.0	0.994118	55.76
H	3.1	1.41	2482.6	6.540	23.95	168.2	0.989412	60.42
J	3.1	0.00	2004.3	5.568	19.60	188.0	0.989474	54.11
K	3.1	0.98	2672.5	5.496	19.20	188.1	0.99	54.20
L	3.1	1.60	3058.6	5.532	19.00	188.4	0.991579	56.13
M	2.8	0.68	2135.0	5.868	20.20	188.3	0.991053	50.63
N	2.7	1.39	2202.9	6.684	21.30	188.5	0.992105	48.80
T	2.25	0.00	2129.3	3.804	21.4	166.9	0.981765	62.45
U	2.22	1.02	3176.5	3.672	21	167.4	0.984705	54.88
V	2.06	1.54	3323.1	3.900	17.5	168.9	0.993529	52.10
W	2.01	0.84	2435.9	4.212	22.7	168.6	0.991765	55.29
X	2.1	1.54	3370.4	3.888	17.50	169.0	0.994118	53.17
O	3.6	0.00	2991.7	4.332	20.00	169.0	0.994118	55.01
P	3.4	1.03	3886.0	4.104	19.60	169.3	0.995882	52.52
Q	3.4	1.70	4157.6	4.416	19.80	170.0	1.00000	54.51
R	3.2	0.71	3023.2	4.656	20.90	169.0	0.994118	58.71
S	2.9	1.49	2766.8	5.712	21.80	169.0	0.994118	56.80

Effect of the rotational barrel segment (RBS) speed

This subsection evaluates how the rotational barrel segment (RBS) speed and direction affect distributive and dispersive mixing under the base operating conditions of $N = 70$ rpm and 170°C (runs A–H, Table 1). Negative N_b values correspond to counter-rotation relative to the screw, whereas positive N_b values correspond to co-rotation.

Figure 5 shows that RBS rotation mainly affects distributive mixing. The baseline case A ($N_b = 0$) yields $\text{DMI} = 67.13 \pm 2.68$ and $\text{DsMI} = 48.58 \pm 7.32$, indicating moderate spatial uniformity and more variable dispersive performance across sampling locations. When the RBS rotates in counter-rotation, the distributive index increases consistently: runs B–D reach DMI values between 71.89 and 74.90, with the best overall result obtained for D ($N_b = -50$), where MixScore reaches 61.61 ± 4.72 . In contrast, mild co-rotation is unfavorable for overall mixing: run F ($N_b = +10$) gives the lowest MixScore in

this subset (52.50 ± 2.43), mainly because DMI decreases to 58.28 ± 6.71 . At higher positive speed, the response changes: run H ($N_b = +50$) reaches $\text{MixScore} = 60.42 \pm 3.25$ and shows the highest dispersive index among runs A–H ($\text{DsMI} = 52.72 \pm 3.74$), while DMI returns to a level close to the baseline. Overall, these results indicate that counter-rotation is more effective at improving distribution uniformity, whereas strong co-rotation can improve control of the dispersive tail.

The histograms in Figure 6 support this interpretation. Relative to the baseline case A, the counter-rotating condition D ($N_b = -50$) maintains a favorable particle-size distribution while improving the spatial uniformity reflected in DMI (i.e., the differences between the size of the particle distribution at 50x and 100x are smaller). In contrast, the strong co-rotating condition H ($N_b = +50$) shows a more favorable upper-tail behavior at 100x (i.e., a higher number of particles for smaller sizes), which is consistent with its higher DsMI. Therefore, the histogram comparison helps explain why the best counter-rotating and co-rotating conditions do not improve mixing in

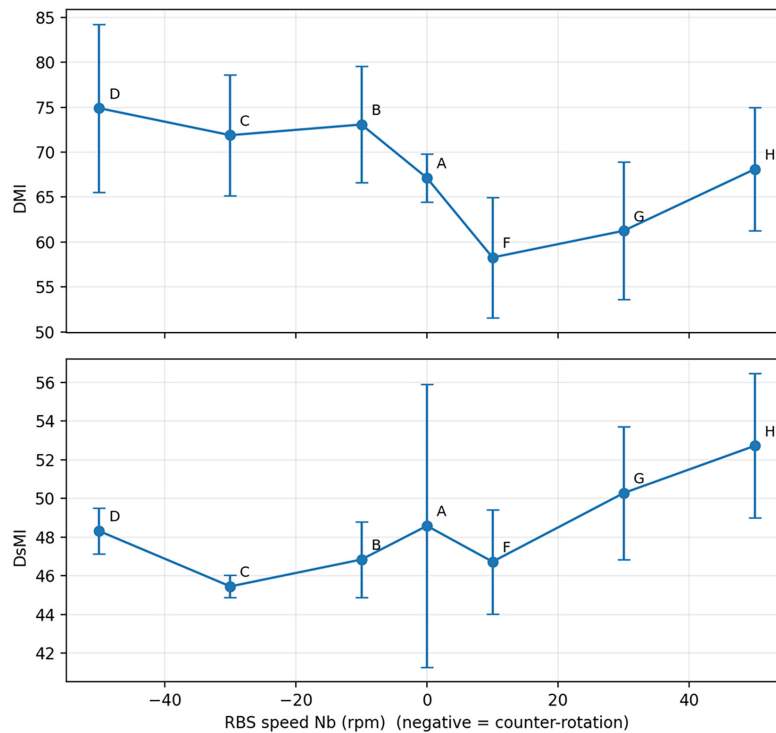


Figure 5. DMI and DsMI vs RBS speed Nb for runs A–H (mean $\pm$ SD across 3 locations)
Error bars represent the standard deviation across the three within-run sampling locations ($n = 3$);
differences between conditions are interpreted as trends

exactly the same way: D is mainly associated with better distributive mixing, whereas H is mainly associated with better dispersive mixing.

Figure 7 and Tables 3 and 4 show that these mixing changes occur together with clear process trade-offs. From A to D, the increase in MixScore is accompanied by an increase in total specific mechanical energy, from 2590.9 to 3443.9 kJ/kg, mainly due to the additional power required to rotate the RBS. In this counter-rotating range, the output remains nearly constant, so the mixing improvement is obtained primarily at the expense of higher energy input per unit mass. In contrast, run H combines a high MixScore with lower specific energy (2482.6 kJ/kg) and the highest throughput in the A–H subset ($Q = 6.54$ kg/h), despite the significant contribution of RBS power. This indicates that strong co-rotation can provide a favorable compromise among dispersive performance, productivity, and energy demand, even though it does not improve distributive mixing as much as strong counter-rotation does.

Within the operating window examined here, adding active RBS rotation is clearly beneficial compared to the neutral condition, but the effect depends on the rotation mode. Counter-rotation provides the most consistent improvement in

distributive mixing and yields the highest overall MixScore at $Nb = -50$, although with a higher energy penalty. Strong co-rotation, on the other hand, provides the best dispersive performance and achieves a high overall score together with higher throughput and lower specific energy. Thus, the preferred operating condition depends on whether the primary objective is spatial uniformity, agglomerate-tail reduction, or a compromise between mixing quality and process efficiency.

This distinction between counter-rotating and co-rotating operation is important for the subsequent analysis, because later sections show that temperature level and downstream mixing geometry modify these two modes differently.

The results further suggest that the co-rotating operation of the RBS improves dispersive mixing not only by changing the average shear intensity but also by modifying the local velocity field in the sleeve channel. In the co-rotating configuration, the relative velocity between the screw and sleeve surfaces is reduced; however, the flow in the rotating channel develops a more complex structure, with elevated shear and extensional stresses near the channel edges. This may promote more effective breakup of pigment agglomerates, even if the overall flow character is closer

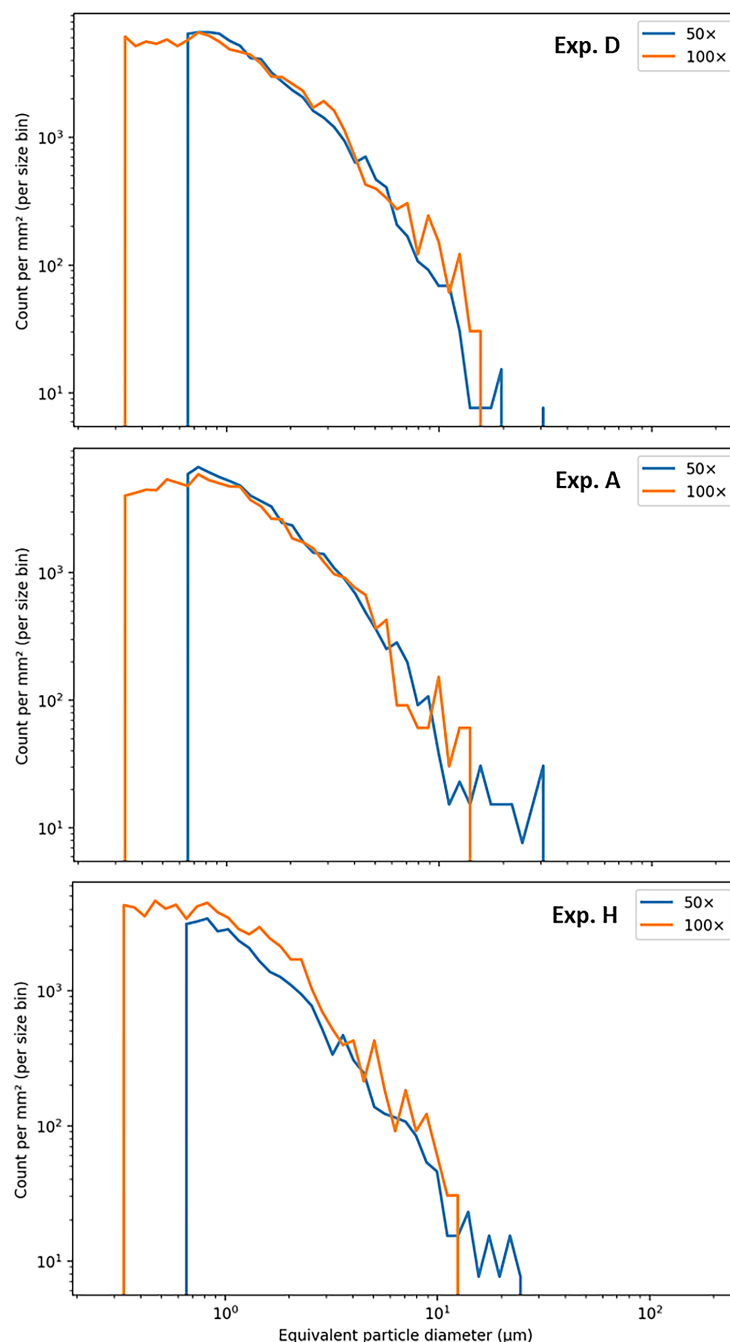


Figure 6. Particle-size histograms (counts/mm²) for runs D (Nb = -50), A (Nb = 0), and H (Nb = +50), showing 50× and 100×. Histograms use logarithmically spaced size bins on log–log axes; counts are normalized per mm² of analyzed area. The corresponding number of detected particles and the D50/D90/D95/Dmax values for each run are reported in the Supplementary Material

to transport than to intensive mixing in the classical sense. Consequently, under the conditions examined here, the key factor is not the global value of relative velocity, but rather the local flow topology within the rotating RBS geometry.

It should be noted that, given the within-run nature of the three sampling locations, the differences between runs A, D, and H (e.g., DMI = 67.1 ± 2.7 , 74.9 ± 9.4 , and 68.1 ± 6.9 , respectively) are

interpreted as consistent trends rather than statistically significant differences. The trends, however, are supported by their systematic direction across locations and by independent process measurements.

Effect of barrel temperature

This subsection evaluates how increasing the barrel and die temperatures from 170 °C to 190

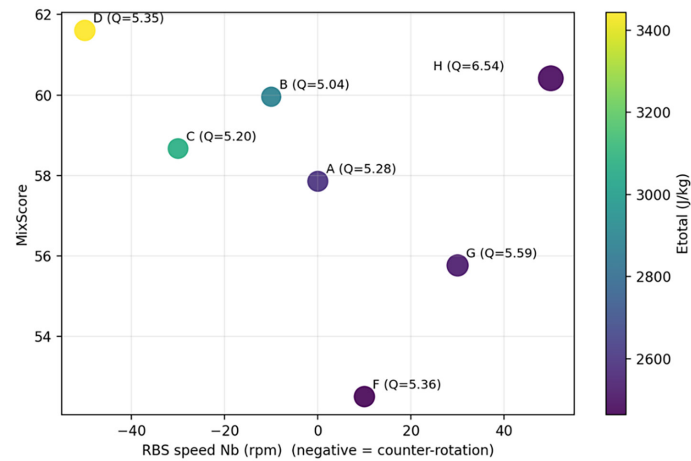


Figure 7. MixScore vs Nb for runs A–H, annotated with output Q and colored by E_{total}

°C affects mixing performance and whether this effect depends on the RBS speed and direction. The comparison is made using matched pairs at the same Nb: A→J (0), C→K (−30), D→L (−50), G→M (+30), and H→N (+50), as summarized in Tables 5 and 6.

Table 5 shows a clear and consistent process response to the higher temperature level. For all matched pairs, the melt temperature measured near the die increases by about 18.5–20.3 °C, confirming that the change in barrel and die set-points is effectively transmitted to the melt. At the same time, the die-entry pressure decreases across all cases by about 1.8–2.7 MPa. The total specific mechanical energy also decreases for all matched pairs, and the output tends to increase slightly. Taken together, these trends are consistent with a lower-viscosity operating state at 190 °C, characterized by reduced pressure demand and lower specific energy input.

Mechanistically, these observations are consistent with the effect of temperature on melt viscosity. At 190 °C, the lower viscosity reduces the shear stresses transmitted to the melt and the total laminar strain accumulated along the screw, weakening the interfacial-area generation that governs distributive mixing. The slightly higher output further reduces the mean residence time, shortening the deformation history. For dispersive mixing, agglomerate rupture requires a critical stress, so the lower viscous stresses at 190 °C would also be expected to hinder breakup; the improvement observed only at Nb = −30 rpm suggests that, in that case, the flow reorganization induced by counter-rotation locally compensates for the loss of viscous stress.

The effect of temperature on mixing, however, is not uniform and depends strongly on Nb. As shown in Table 6 and Figure 8, the distributive mixing index (DMI) decreases for all matched pairs as temperature increases. The reduction is moderate in the neutral and counter-rotating cases and becomes especially pronounced at high positive RBS speeds, where H→N shows the largest drop in DMI. This result indicates that higher temperatures are systematically unfavorable for distribution uniformity within the operating window examined here.

In contrast, the effect of temperature on dispersive mixing (DsMI) is smaller and depends on the RBS condition. Figure 8 and Table 6 show that the neutral and positive-Nb cases exhibit only minor changes in DsMI, whereas the intermediate counter-rotating case C→K (Nb = −30) shows a clear improvement. Therefore, the temperature increase does not produce a general dispersive benefit; instead, it improves dispersive performance only under a specific RBS condition. As a consequence, the combined MixScore decreases for all matched pairs, although the magnitude of this decrease depends on the balance between DMI loss and DsMI change.

Figure 9 provides microstructural support for these trends. For the pair C vs K at Nb = −30, the histograms show a reduction in the upper particle-size tail at 100× when the temperature is increased, which is consistent with the increase in DsMI. In contrast, for the H vs N pair at Nb = +50, the histograms do not show a comparable tail improvement; instead, the dominant effect is a marked decrease in DMI. These results reinforce that the effect of temperature cannot be described by a single “mixing improvement” trend, because the distributive and dispersive responses do not evolve in the same way.

Table 5. Process changes for matched Nb pairs: differences between 190 °C and 170 °C values.

Nb (rpm)	LowT ID	HighT ID	ΔT_{b3} (°C)	ΔT_4 (°C)	ΔP_4 (MPa)	ΔE_{total} (kJ/kg)	ΔQ (kg/hr)
-50	D	L	20	19.2	-2.4	-385.30	0.18
-30	C	K	20	19.1	-1.8	-396.79	0.3
0	A	J	20	18.5	-1.85	-586.6	0.29
30	G	M	20	19.3	-2.2	-388.64	0.28
50	H	N	20	20.3	-2.65	-279.70	0.14

Table 6. Mixing-index changes for matched Nb pairs: differences between 190 °C and 170 °C values.

The /SE columns normalise each change by the magnitude of the specific-energy change, $|\Delta E_{total}|$ (in MJ/kg)

Nb (rpm)	ΔDMI	$\Delta DsMI$	$\Delta Mix\ Score$	$\Delta DMI/SE$	$\Delta DsMI/SE$	$\Delta Mix/SE$
-50	-10.76	-0.19	-5.48	-27.93	-0.49	-14.22
-30	-15.74	6.80	-4.47	-39.67	17.14	-11.27
0	-6.89	-0.61	-3.74	-11.75	-1.04	-6.38
30	-9.95	-0.31	-5.13	-25.60	-0.80	-13.20
50	-23.14	-0.09	-11.62	-82.73	-0.32	-41.54

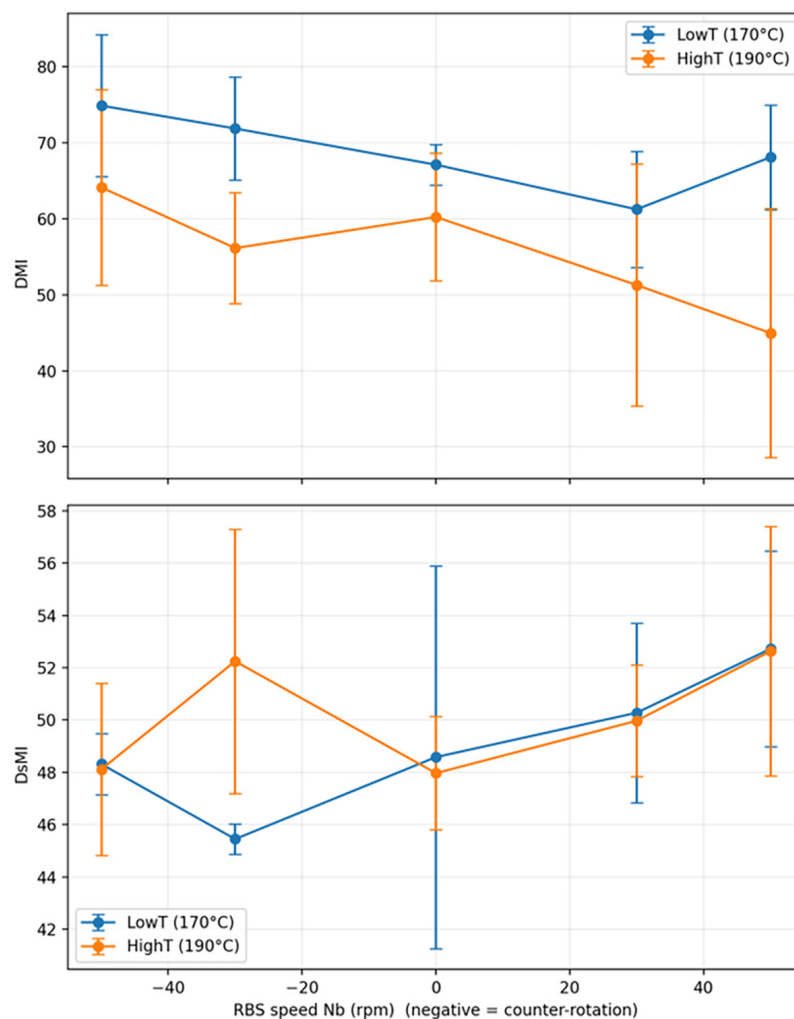


Figure 8. Interaction plots of DMI and DsMI versus Nb at 170 °C and 190 °C (mean $\pm$ SD across 3 locations). Error bars represent the standard deviation across the three within-run sampling locations (n = 3); differences between conditions are interpreted as trends

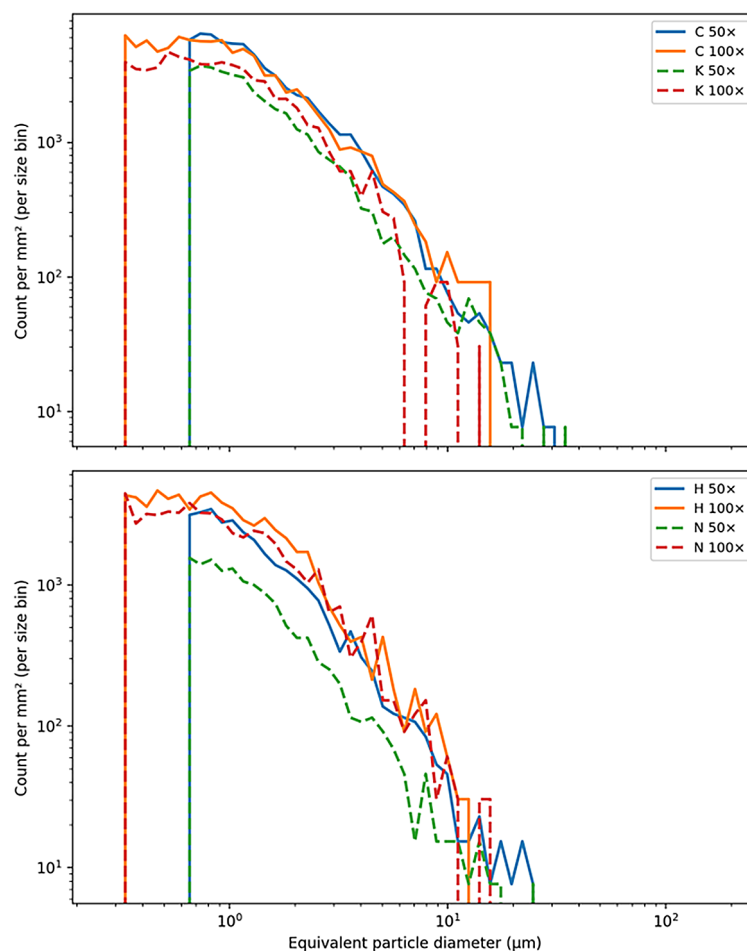


Figure 9. Matched temperature histograms (counts/mm²): C vs K at Nb = −30 and H vs N at Nb = +50 (50× and 100×). Histograms use logarithmically spaced size bins on log–log axes; counts are normalized per mm² of analyzed area. The corresponding number of detected particles and the D50/D90/D95/Dmax values for each run are reported in the Supplementary Material.

Overall, increasing the barrel and die temperatures from 170 °C to 190 °C yields a consistent process benefit in terms of lower pressure and specific energy, but this does not translate into a uniform mixing benefit. Under the tested conditions, the higher temperature systematically reduces distributive mixing, whereas dispersive mixing improves only in the intermediate counter-rotating case (Nb = −30). Therefore, temperature should be treated as a selective process variable that modifies the balance between mixing quality and process efficiency, rather than as a universally favorable condition for mixing.

Effect of reduced screw speed

This subsection isolates the effect of the screw rotational speed by repeating the full RBS speed and direction sweep at a reduced screw speed of N = 50 rpm, while keeping the barrel and die

temperature fixed at 170 °C (runs T–X, Table 1). These runs are directly comparable, at matched RBS speed and temperature, to the base series obtained at N = 70 rpm (runs A–H). The comparison is therefore organised as matched pairs at the same N_b: A→T (N_b = 0), C→U (N_b = −30), D→V (N_b = −50), G→W (N_b = +30), and H→X (N_b = +50). Negative N_b values correspond to counter-rotation and positive values to co-rotation relative to the screw. The corresponding mixing indices are reported in Table 3.

Within the reduced-speed series, the response to RBS rotation differs markedly from that observed at N = 70 rpm. The neutral condition T (N_b = 0) provides the highest distributive index and the highest overall score of the entire reduced-speed series (DMI = 79.32 ± 1.43, MixScore = 62.45 ± 0.95), together with the lowest location-to-location scatter. Activating the RBS at this lower screw speed does not

improve distributive mixing; on the contrary, it consistently lowers DMI relative to the neutral case. Counter-rotation produces the strongest reduction, with V ($N_b = -50$) giving the lowest DMI of the series (52.73 ± 6.23), while co-rotation shows an intermediate behaviour (W, DMI = 64.28; X, DMI = 55.93). The dispersive index follows the opposite, but much weaker, trend: the strongest rotations in either direction yield the best tail control (V, DsMI = 51.48; X, DsMI = 50.41), whereas the neutral and mild conditions remain close to DsMI ≈ 45.6 –46.3. Because the dispersive changes are small and the distributive changes are large, the overall MixScore at N = 50 rpm is governed mainly by the distributive response and is therefore highest for the neutral condition T.

The matched-pair comparison with the N = 70 rpm series clarifies how screw speed interacts with RBS operation. Under neutral RBS (A→T), reducing the screw speed clearly improves distributive uniformity (DMI from 67.13 to 79.32, Δ DMI = +12.19) at the cost of a small dispersive penalty (DsMI from 48.58 to 45.57), giving a net increase in MixScore (+4.60). In contrast, when the RBS is activated, reducing the screw speed degrades the distributive performance that was beneficial at N = 70 rpm. This is most pronounced for the strongest counter-rotating pair D→V ($N_b = -50$), where DMI falls from 74.90 to 52.73 (Δ DMI = -22.17) and MixScore drops by 9.51 points, with only a modest dispersive gain (Δ DsMI = +3.17). The intermediate counter-rotating pair C→U and the strong co-rotating pair H→X show the same qualitative tendency (Δ DMI = -8.43 and -12.18, respectively), whereas the mild co-rotating pair G→W is almost neutral overall (Δ MixScore = -0.47), as a small distributive gain is offset by a dispersive loss.

Taken together, these results indicate that the favourable role of RBS rotation identified at N = 70 rpm is strongly screw-speed-dependent. At the base screw speed, activating the RBS — particularly in counter-rotation — enhanced distributive mixing relative to the neutral condition; at the reduced screw speed, the neutral condition already delivers the best distributive uniformity, and imposing barrel rotation no longer helps and generally impairs it. A plausible interpretation, consistent with the kinematic view of laminar mixing adopted throughout this work, is that the relative motion between the screw and the rotating

sleeve, rather than the absolute RBS speed, controls the local deformation history. At N = 50 rpm the lower drag-driven throughput weakens cross-sectional renewal, and the imposed sleeve rotation appears to promote a more recirculating, less effectively redistributed flow than at N = 70 rpm. Because residence-time-distribution measurements were not performed, this mechanistic explanation is offered qualitatively and would benefit from dedicated flow characterization in future work.

These mixing trends must also be read against the process penalties of operating at reduced screw speed. The N = 50 rpm runs deliver substantially lower output than their N = 70 rpm counterparts ($Q \approx 3.7$ –4.2 kg/h versus 5.0–6.5 kg/h), so any change in mixing is achieved at a clear productivity cost. Among the reduced-speed runs, the neutral case T also has the lowest total specific mechanical energy (≈ 2129 kJ/kg, with no RBS power contribution), whereas activating the RBS raises the specific energy without an accompanying distributive benefit; the counter-rotating case V, for example, reaches ≈ 3323 kJ/kg while giving the lowest DMI of the series. Consequently, at N = 50 rpm there is no operating point that simultaneously improves distributive mixing, dispersive mixing, throughput, and energy demand relative to the neutral baseline. The reduced screw speed is therefore advantageous for distributive uniformity only when the RBS is left neutral; once the RBS is activated at this speed, the additional energy input and the loss of throughput are not compensated by improved mixing. This contrasts with the N = 70 rpm behavior, reinforcing the central finding of the study: namely, that the RBS acts as an effective active mixing variable only within a suitable operating window, and that its benefit cannot be assessed independently of screw speed, temperature, and the targeted mixing objective.

Effect of using a mixing device

This subsection evaluates whether replacing the downstream screw section with a Cut Rings mixing section improves the final mixing state delivered by the rotational barrel segment (RBS). The comparison is made using matched operating conditions at N = 70 rpm and 170 °C, namely A vs O ($N_b = 0$), C vs P ($N_b = -30$), D vs Q ($N_b = -50$), G vs R ($N_b = +30$), and H vs S ($N_b = +50$). In the RBS-only configuration (A–H), the downstream length L5 + L6

corresponds to a conventional screw section, whereas in the RBS + Cut Rings configuration (O–S), the downstream region is composed of a screw section followed by a Cut Rings mixing section. This modification changes the downstream flow topology and may affect both spatial redistribution and agglomerate breakup.

Figure 10 shows that the effect of the Cut Rings device is nonuniform and strongly depends on the RBS operating conditions. For the neutral case (A vs O), the Cut Rings configuration reduces DMI from 67.13 ± 2.68 to 62.09 ± 2.59 , while DsMI remains essentially unchanged, leading to a small decrease in MixScore. For the

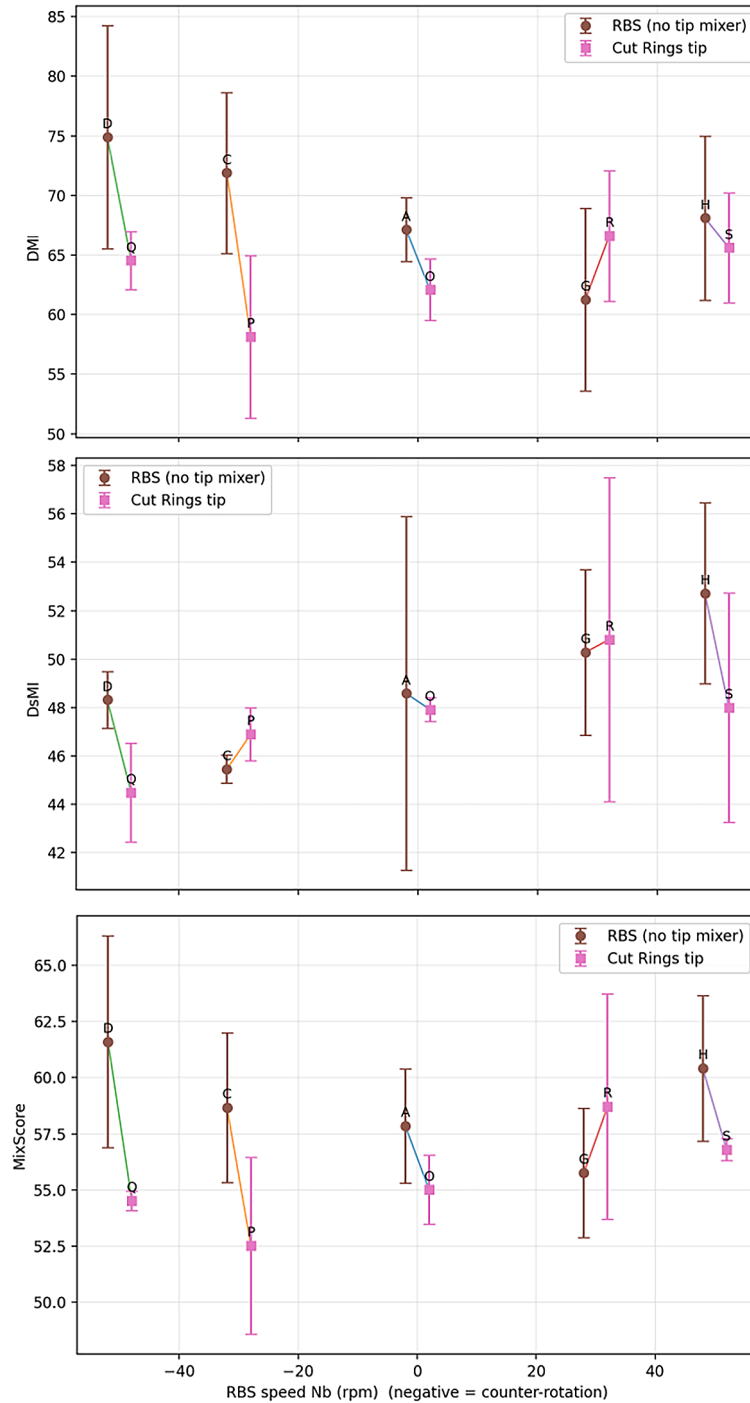


Figure 10. Distributive mixing index (DMI, DsMI, and MixScore) comparison between RBS-only (A, C, D, G, H) and RBS + Cut Rings (O, P, Q, R, S) at matched Nb. Error bars represent the standard deviation across the three within-run sampling locations ($n = 3$); differences between conditions are interpreted as trends.

counter-rotating cases, the Cut Rings section does not improve the final mixing state. At $Nb = -30$ (C vs P), DMI decreases markedly, and MixScore also decreases, while DsMI changes only slightly. At $Nb = -50$ (D vs Q), both DMI and DsMI decrease, producing one of the clearest negative effects of the additional mixing device. These results indicate that, under neutral and counter-rotating RBS operation, the RBS-only configuration already provides the more favorable final morphology within the tested window.

A different trend is observed for the co-rotating case at $Nb = +30$. In the G vs R comparison, the Cut Rings device increases DMI from 61.25 ± 7.67 to 66.61 ± 5.49 , while DsMI remains essentially unchanged. As a result, MixScore increases from 55.76 ± 2.88 to 58.71 ± 5.03 . This is the clearest case in which the downstream Cut Rings section adds value, suggesting that under this co-rotating condition, the RBS-only configuration does not provide the same level of spatial redistribution achieved when the downstream mixing element is present. At $Nb = +50$ (H vs S), however, the benefit disappears: DMI remains similar within the observed variability, whereas DsMI decreases from 52.72 ± 3.74 to 47.99 ± 4.74 , causing the overall MixScore to fall.

Figure 11 helps explain the negative effect observed at $Nb = -50$ by comparing the particle-size distributions for D and Q. The Cut Rings case does not reduce the upper particle-size tail;

instead, at $100\times$ it shows a heavier tail in the approximate range of $8\text{--}15\text{ }\mu\text{m}$, which is consistent with the lower DsMI measured for Q. Therefore, under the strongest counter-rotating condition tested, the added Cut Rings section does not improve agglomerate breakup and may even preserve a less favorable particle-size tail.

To strengthen the link between downstream geometry and process response, Figure 12 compares the pressure profiles for two representative matched pairs: D vs Q ($Nb = -50$ rpm) and G vs R ($Nb = +30$ rpm), corresponding to the RBS-only and RBS + Cut Rings configurations, respectively. In both comparisons, the overall pressure evolution along the extruder follows the same general pattern: pressure increases from upstream barrel positions to a maximum near the middle of the line, then decreases toward the die region. However, the addition of the Cut Rings section alters the pressure levels, particularly downstream of the extruder. Representative matched cases are shown for clarity; the complete pressure data (P1–P4) for all conditions are reported in Table 5.

For the counter-rotating pair D vs Q, the Cut Rings configuration results in higher pressure in the intermediate region of the extruder, while the pressure near the die remains slightly lower than in the RBS-only case. This indicates that the downstream geometry changes the distribution of pressure build-up along the line, without producing a more favorable final mixing state.

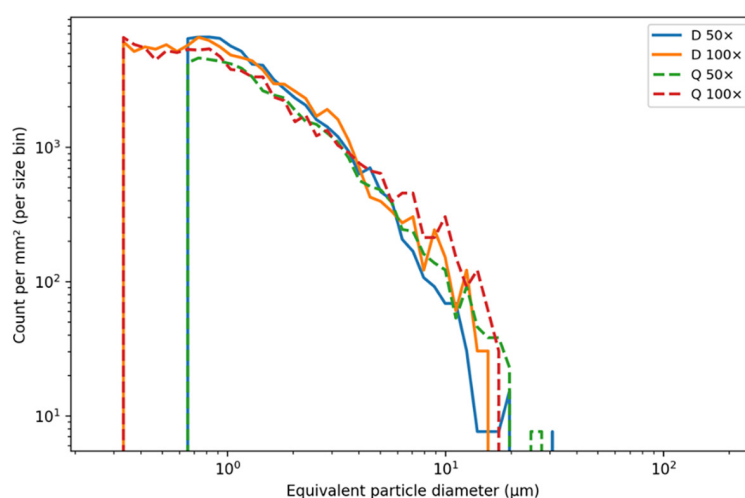


Figure 11. Example of mixing-device impact on particle-size number density (counts/mm² per size bin) for $Nb = -50$ rpm: RBS-only (D) versus RBS + Cut Rings (Q), shown for $50\times$ and $100\times$ magnifications.

Histograms use logarithmically spaced size bins on log–log axes; counts are normalized per mm² of analyzed area. The corresponding number of detected particles and the D50/D90/D95/Dmax values for each run are reported in the Supplementary Material

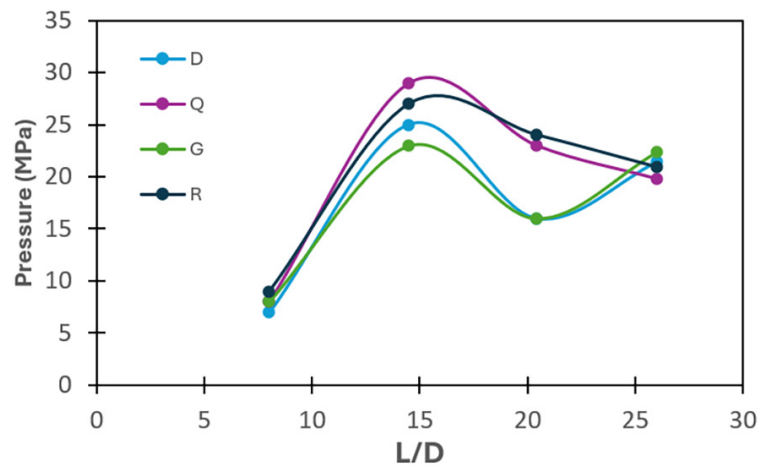


Figure 12. Pressure profiles along the extrusion line for representative matched cases with and without the downstream Cut Rings section: D (RBS, $N_b = -50$ rpm), Q (RBS + Cut Rings, $N_b = -50$ rpm), G (RBS, $N_b = +30$ rpm), and R (RBS + Cut Rings, $N_b = +30$ rpm). Pressure was measured at the four instrumented locations and plotted as a function of axial position (L/D)

This observation is consistent with the microscopy results, which showed that Q exhibited lower DsMI and a less favorable particle-size tail than D. Therefore, the additional downstream pressure demand introduced by the Cut Rings section does not appear to translate into improved agglomerate breakup under this operating condition.

For the co-rotating pair G vs R, the pressure profiles are also shifted due to the presence of the Cut Rings section, with slightly higher pressure levels in the intermediate and downstream regions for R than for G. In this case, the process change is accompanied by improvements in DMI and MixScore, suggesting that the altered downstream flow conditions are beneficial primarily for spatial redistribution rather than for additional dispersive breakup. Thus, the pressure-profile comparison supports the conclusion that the Cut Rings section affects the final mixing state through regime-dependent modifications to downstream flow resistance and pressure build-up.

Figure 12 provides additional process-level evidence that the Cut Rings element changes the extruder's operating state, but its effect on mixing depends on the RBS condition. A higher or redistributed pressure profile does not necessarily imply a better final morphology; instead, the impact of the downstream mixing device must be interpreted in conjunction with the microscopy-based distributive and dispersive indices.

The process data in Table 3 show that the Cut Rings runs generally operate at lower throughput and, in several cases, higher total specific mechanical energy than their matched RBS-only

counterparts. This is particularly evident for P and Q, where the additional energy demand is not accompanied by improved mixing indices. Thus, within the present operating window, the Cut Rings section cannot be regarded as a universally beneficial addition. Its effect is selective: it improves the final result only in the intermediate co-rotating case ($N_b = +30$), primarily through improved distributive mixing, whereas under neutral and counter-rotating conditions it offers no advantage and may even worsen the final morphology.

Overall, the results show that the downstream mixing device must be evaluated together with the RBS operating mode, rather than in isolation. The RBS + Cut Rings configuration is not systematically superior to the RBS-only configuration. Instead, its benefit is regime-dependent and is most apparent when additional downstream redistribution is needed, whereas under conditions where the RBS already performs well, the Cut Rings section may increase energy demand without improving the final mixing state.

Trade-off summary

Table 7 summarizes, in Pareto-style form, the preferred operating condition for each individual process objective. The comparison is restricted to the RBS-only runs at $N = 70$ rpm and 170°C (runs A–H), so that only the RBS rotational speed differs between the conditions compared; the reduced-screw-speed and elevated-temperature runs are treated separately.

Table 7. Preferred RBS operating condition per process objective, among the RBS-only base cases at $N = 70$ rpm and $170\text{ }^{\circ}\text{C}$ (runs A–H).

Objective	Preferred run	Key value
Maximum DMI	D ($N_b = -50$ rpm)	DMI = 74.9
Maximum DsMI	H ($N_b = +50$ rpm)	DsMI = 52.7
Maximum MixScore	D ($N_b = -50$ rpm)	MixScore = 61.6
Minimum Etotal	F ($N_b = +10$ rpm)	Etotal = 2463.1 kJ/kg
Maximum throughput	H ($N_b = +50$ rpm)	Q = 6.54 kg/h
Mixing/energy/throughput compromise	H ($N_b = +50$ rpm)	MixScore = 60.4; Etotal = 2482.6 kJ/kg; Q = 6.54 kg/h

CONCLUSIONS

This work evaluated the mixing performance of a single-screw extrusion system incorporating a rotational barrel segment (RBS) and quantified the effects of RBS kinematics, barrel/die temperature, and a downstream Cut Rings mixing section on distributive mixing, dispersive mixing, and process trade-offs during the dilution of a blue masterbatch in LDPE.

For the RBS-only configuration, activation of the rotational barrel segment significantly modified the final mixing state relative to the neutral condition. Counter-rotation generally improved distributive mixing, leading to higher DMI values and to the highest overall MixScore at the most intense counter-rotating condition tested ($N_b = -50$ rpm). In contrast, co-rotation showed a non-monotonic response: a mild positive N_b reduced overall mixing performance, whereas strong co-rotation ($N_b = +50$ rpm) produced the highest dispersive index among the base cases, combining good overall mixing with the highest throughput and comparatively low specific energy. These results show that the preferred RBS operating condition depends on the targeted mixing objective. Counter-rotation is more favorable when spatial uniformity is the main requirement, whereas strong co-rotation is attractive when dispersive tail reduction and process productivity are prioritized.

Drawing on the trade-off summary of Section 4.6 (Table 7), the results support the following guidelines for practitioners: (i) when colour or shade uniformity is the primary objective, strong counter-rotation ($N_b = -50$ rpm) at $170\text{ }^{\circ}\text{C}$ is preferred, and the Cut Rings section should be avoided; (ii) when agglomerate dispersion at high throughput is the priority, strong co-rotation ($N_b = +50$ rpm) at $170\text{ }^{\circ}\text{C}$ is recommended, offering the highest DsMI and output at comparatively

low specific energy; (iii) when specific-energy minimisation dominates, mild co-rotation or the neutral condition should be used, accepting a lower mixing score; and (iv) the Cut Rings section should be considered only in combination with intermediate co-rotation ($N_b = +30$ rpm), where it improved distributive mixing.

Increasing the barrel and die temperatures from $170\text{ }^{\circ}\text{C}$ to $190\text{ }^{\circ}\text{C}$ produced a consistent process response: higher melt temperature, lower die-entry pressure, lower specific energy, and slightly higher output. However, this improved processability did not translate into a general improvement in mixing. Within the tested operating window, higher temperature systematically reduced distributive mixing, while dispersive mixing improved only in the intermediate counter-rotating case ($N_b = -30$ rpm). Therefore, the effect of temperature must be regarded as selective: it shifts the balance between process efficiency and mixing quality, rather than uniformly improving mixing.

The comparison between the RBS-only configuration and the RBS + Cut Rings configuration showed that the downstream mixing device is not universally beneficial. Its effect depends strongly on the RBS operating mode. Under neutral and counter-rotating conditions, the Cut Rings section did not improve the final morphology and, in some cases, reduced both DMI and DsMI. The clearest benefit was observed at $N_b = +30$ rpm, where the Cut Rings section improved distributive mixing and increased MixScore. The additional pressure-profile comparison for representative matched cases further supported the conclusion that the Cut Rings section modifies downstream pressure build-up and flow resistance, but that these process changes do not necessarily lead to better final dispersion or distribution. Thus, the downstream device must be evaluated together with the RBS condition, rather than as an intrinsically superior configuration.

From a practical standpoint, these results highlight that conventional downstream mixing elements, such as Cut Rings tips, are not an automatic improvement to a configuration with an active barrel. Under neutral and counter-rotating conditions, the use of Cut Rings leads to lower DMI and DsMI values while increasing energy demand and reducing throughput, indicating an unfavorable process trade-off. An improvement in mixing quality is observed only for selected co-rotating conditions, in which the local deformation field generated by the Cut Rings complements, rather than competes with, the action of the RBS. This implies that the design of the downstream mixing configuration must be tightly coordinated with the RBS kinematics, and that potential negative interactions between active and passive mixing elements need to be considered already at the process design stage.

In general, the results demonstrate that the RBS is an effective active mixing variable in single-screw extrusion, capable of shifting the balance between distributive and dispersive mixing according to its speed and direction. The study also shows that microscopy-based image analysis provides a practical route for quantifying these two aspects separately and relating them to measurable process variables. This is particularly important because a single “best mixing condition” does not exist independently of the process objective: the preferred operating point depends on whether the main priority is shade uniformity, agglomerate-tail reduction, energy efficiency, or throughput.

The present work has some important limitations that should be recognized. First, the interpretation of flow-history effects is based on measured process variables and operating conditions, since residence-time-distribution measurements were not performed in this study. Second, the mixing indices depend on the image-analysis procedure adopted, including segmentation and feature-detection criteria, although the same workflow was applied consistently across all runs. In addition, the mean $\pm$ SD values are based on three within-run sampling locations rather than independent replicate runs, so formal significance testing between conditions was not performed. Third, the conclusions are based on a blue masterbatch/LDPE system, which is suitable for comparative assessment but does not capture all dispersion problems encountered in polymer extrusion.

Future work should therefore proceed in three directions. First, targeted RTD measurements

should be conducted under representative operating conditions to strengthen the mechanistic interpretation of the observed mixing trends. Second, the methodology should be extended to a more demanding dispersive system, such as TiO₂ in the same LDPE matrix, and to alternative image-based mixing metrics, including area-fraction uniformity, color-uniformity measures, and defect-density descriptors. Together, these developments would improve the robustness of the analysis and support future optimization and design of active mixing systems for extrusion.

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