AI-assisted monitoring of coal particles within droplets in a coal monoethylene glycol slurry spray

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1) Novelty Statement

In this work, we present a novel approach that applies the Time-Shift Time-of-Flight (TSTOF) technique for the sensitive analysis of complex droplets in sprays. The method was validated through experimental measurements on a coal monoethylene glycol slurry spray. By capturing and processing light scattering signals from the TSTOF instrument, the approach enables precise monitoring of the mass concentration of suspended particles within droplets and provides an estimate of their average particle size. To fully exploit the temporal structure of the signals, the data were represented as tensors and analyzed using a convolutional neural network (CNN), establishing an AI-driven framework for advanced spray characterization.

2) Significance Statement

Measuring droplets in slurry sprays is crucial for understanding and optimizing conversion processes in high-pressure entrained-flow gasifiers. The composition and particle content of these droplets strongly influence atomization, evaporation, and subsequent reaction behavior, which in turn determine syngas quality and process efficiency. This highlights the urgent need for advanced diagnostic techniques capable of characterizing droplet composition and suspended particle properties. In this work, we present a novel method designed for such analysis. The presented method can specifically monitor coal monoethylene glycol slurry sprays, enabling a more detailed understanding of the combustion process and supporting the development of efficient and reliable gasification technologies.

3) Author Contribution

- Walter Schäfer *wrote paper, designed research*
- Tobias Jakobs *wrote paper, experimental realization*
- Patrick Stegmann *wrote paper, analyzed data*

4) Preferred Presentation Format

We would like to give both a poster and an oral presentation. In any case, we will prepare a graphical abstract in the form of a poster. This way, I can deliver the oral presentation, and if there is space for a poster, I would also present it.

5) Colloquium/Colloquia Designation and Keywords

Colloquium choices (order of preference): 1) Heterogeneous combustion and processes, 2) Diagnostics and experimental methods, 3) Energy and material conversion and heating processes.
Keywords: Coal; Slurry spray; Concentration; Particle sizing; Artificial intelligence; Measurement technique

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Abstract

We present a novel method for characterizing the average size and mass concentration of coal particles within droplets in a coal monoethylene glycol slurry spray. The method is based on the analysis of continuous light scattering signals from individual droplets interacting with a shaped light beam. The experimental setup employs four detectors that collect scattered light at different angles, generating four distinct data streams corresponding to the droplet flow. These signals are transformed into Particle-Tensor-AI (PTA) representations, which can be constructed in various formats. In this work, we implement a format in which detector signals are mapped into RGB images, with each color channel representing a specific detector. The PTAs, labeled with the average coal particle size and mass concentration, are used to train convolutional neural networks (CNNs) for classification tasks. Various detector combinations, downsampling strategies, and material conditions were investigated. Validation experiments demonstrated proof-of-principle feasibility, achieving prediction accuracies up to 95%. This approach enables trigger-free, information-preserving analysis of light scattering data, offering strong potential for advanced diagnostics not only in coal monoethylene glycol sprays but also in other droplet and particle flows.

Keywords: Coal; slurry spray; Concentration; Particle sizing; Artificial intelligence; Measurement technique

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1. Introduction

The theoretical foundations of light scattering from droplets in shaped light beams, such as Gaussian beam, have been extensively studied in [1,2]. In this work, we investigated the phenomenon experimentally by employing a Time-Shift Time-of-Flight (TSTOF) instrument to generate light-scattering signals from dynamic coal monoethylene glycol slurry droplets in a spray, where the droplets pass sequentially through two shaped light beams with different polarizations. TSTOF was first introduced as a ready-to-use device in 2012 at TU-Darmstadt [3], combining the Time-Shift (TS) and Time-of-Flight (TOF) techniques. While the optical TOF principle is long established and has no single inventor, TS was first reported by Semidetnov (1985) [4] and Pavlovskii (1991) [5]. It was further developed in several dissertations at TU-Darmstadt, including those of Damaschke (2003) [6], Bakis (2010) [7], Kretschmer (2011) [8], Schäfer (2012) [3], Stegmann (2015) [9], Rosenkranz (2016) [10], and Li (2020) [11]. Additional refinements came from external works such as Wigger et al. (2018) [12], Weich (2021) [13], Wachter (2023) [14], and Gödeke

(2023) [15]. Commercial TSTOF devices are marketed under the brand names SpraySpy® [16] SprayQuantAI®, ParticleTensorAI® [17]. The practical application of the time-shift technique for suspension droplet characterization, particularly for determining suspension concentration, was first demonstrated by Albrecht (2009) [2], Schäfer (2014) [18], Kuhnhenn (2016) [19], Rosenkranz (2016) [20], and Li (2020) [21]. These studies expanded the theoretical understanding of light scattering in suspension droplets. Furthermore, the potential of TSTOF for measuring dust and ice crystals was shown by Stegmann (2016) [22].

TSTOF enables determination of droplet size and velocity through real-time analysis of scattering signals in counting mode, where each droplet is detected and analyzed individually. A characteristic scattering signal is recorded, and specific parameters such as size and velocity are extracted for this single droplet. Techniques such as PDA [23, 24], TSTOF [3], and various imaging-based approaches all belong to counting methods, which are highly effective for basic droplet sizing and velocity measurements. However, they face limitations when applied to more

complex physical and chemical properties, such as the refractive index of multicomponent liquids, the solid content of slurry droplets, or the pigment loading of paints. Moreover, these methods often rely on pre-selection of signal segments controlled by triggering mechanisms and validation filters. While this ensures data quality, it can also result in the loss of valuable information, reduced sensitivity, and limited applicability in dense, turbulent, or highly dynamic sprays.

To address these challenges, we propose a trigger-free, AI-based analysis of continuous light scattering signals. Instead of evaluating each droplet independently, the buffered light scattering signals from TSTOF devices are represented as particle-tensor-AI (PTA) structures [25], which preserve the complete temporal information from ensembles of droplets. PTAs can be generated in various formats; one practical implementation maps detector signals into RGB images, with each detector assigned to a specific color channel. This representation enables the direct application of CNNs originally developed for image analysis. However, RGB is only one possible format, and alternative tensor encodings may offer advantages for specific applications.

2. Experimental Setup

The measurement data used in this study were obtained in a previous investigation published in [26], conducted with the ATMOspheric spray test rig (ATMO) at the KIT/ITC facility, described in detail in [27] and shown in Fig. 1. A twin-fluid lance was supplied with liquid or suspension through an eccentric screw pump, regulated by a Coriolis mass flow and density meter. A stirred liquid storage tank prevented sedimentation. The atomizing air mass flow was controlled by a hot-wire anemometer in combination with a valve. To avoid recirculation of small droplets caused by exhaust suction, a honeycomb structure was installed at the inlet of the collection tank to act as a flow straightener.

The twin-fluid atomizer consisted of a central tube with a diameter of 2 mm and a surrounding gas slit of 2.06 mm. For spray characterization, the TSTOF measurement instrument was used. A photograph of the experimental setup is shown in Fig. 2, including the nozzle and the measurement head of the TSTOF instrument. The spray parameters were kept constant at **dV/dt = 7.5m³/h** and **dM/dt = 12.56kg/h**. The measurement position was fixed: horizontally centered with respect to the nozzle axis and vertically 120 mm downstream of the nozzle exit. Experiments were carried out with three slurry concentrations (**Cm = 5%, 10%, 20%**) and three coal particle sizes (**SMDp = 4.0µm, 9.4µm, 18.7µm**). In total, five measurements were performed, analyzing coal monoethylene glycol slurry sprays and generating two datasets. The first dataset, reported in [26], includes droplet properties such as size, velocity, and opacity

factor, while the second dataset contains buffered light-scattering signals, which are the focus of this study.
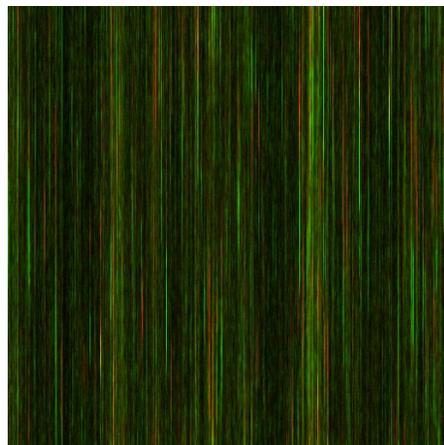

Fig. 1: Example of PTA as an RGB image with 3x1024x1024 dimensions with the vertical time flow with resolution of 6.4ns and total time of 6.7ms [25].
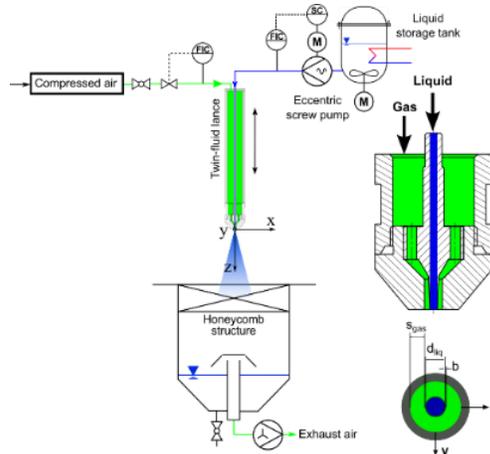

Fig. 2: Schematic view of the atmospheric spray test rig (ATMO) with the applied twin-fluid nozzle [27].

Light-scattering signals were recorded with a high-speed digitizer at 156.3MSa/s (6.4 ns sampling interval) and a buffer length of 15.6MSa (100ms), corresponding to approximately 700 droplet events per buffer. A similar acquisition strategy has been reported in [28]. After acquisition, the buffered signals represent a continuous sequence of droplet events registered by the TSTOF instrument. In conventional counting techniques such as PDA [23, 24], TSTOF, or imaging-based methods, only signals that can be clearly attributed to individual droplets are processed, while large portions of the data stream are discarded. This is typically enforced by predefined triggering thresholds and validation filters, which
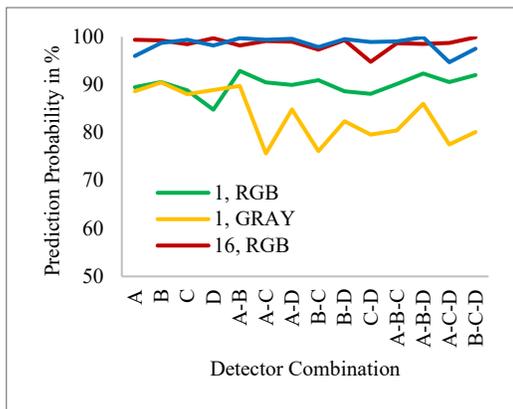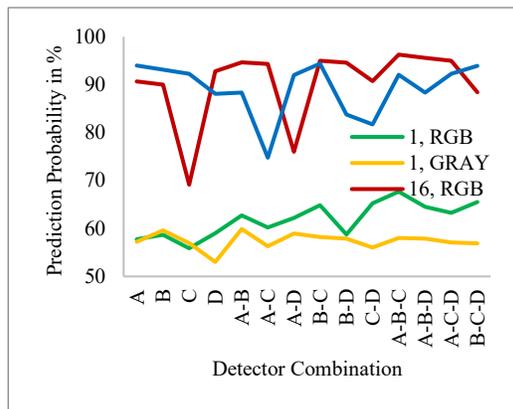
Fig. 3: Cm classification.

Fig. 4: SMDp classification.

exclude weaker signals from analysis. Such constraints limit applicability across different droplet and particle types or operating conditions. By eliminating triggering and validation steps, additional scattering information can be preserved, resulting in significantly higher sensitivity for diagnostics of flows, sprays, droplets, and particles.

To overcome these limitations, buffered signals from four detectors were segmented and combined into tensors, referred to as Particle Tensor AI (PTA) [25]. The tensor dimensions were defined by the number of detectors, the segment length, and the number of segments. In this study, PTAs with three channels were generated to allow representation as RGB images, with detector signals mapped to the red, green, and blue channels (e.g., detector A to red, detector B to green, and detector C to blue). This transformation produces image-like structures directly compatible with convolutional neural network (CNN) analysis (Fig. 1). Representing PTAs as RGB images enables the use of powerful image-processing techniques originally developed for applications such as face recognition and other pretrained neural networks. Moreover, the light-scattering stream can be transformed into video-like sequences and analyzed with AI methods for highly sensitive monitoring of particles, droplets, and flow parameters. In this study, PTAs were also mapped against the composition of the coal monoethylene glycol slurry to monitor the spraying process.

The PTA concept was developed to capture the full temporal and spatial complexity of light-scattering signals generated by droplet ensembles. In contrast to traditional methods, all information from weak, overlapping, or irregular signals is retained and available for analysis. PTA construction begins with simultaneous acquisition of light-scattering signals from multiple detectors positioned at defined angles. In this study, four detectors were used. The continuous signal stream from these detectors was divided into fixed-length segments, which were stacked to form tensors representing defined time

windows that may contain one or more droplet events. These tensors encode temporal variations in scattering intensity as structured data and can be visualized as image-like patterns once mapped into RGB channels.

3. AI Calculation

In this work, the predictive capability of PTAs was evaluated for determining the mass concentration and mean particle size of coal particles suspended in a coal monoethylene glycol slurry. All AI models were trained in classification mode. Due to hardware limitations, PTAs were restricted to dimensions of $3\times256\times256$ with 8-bit resolution, corresponding to 256-sample segments and 256 segments per tensor. The temporal coverage was defined as $T = 256\times256\times dt$, where dt is the sampling interval. Based on previous measurements, droplet velocities averaged about 30 m/s with mean diameters of 120 µm [26], yielding maximal light-scattering signal lengths of approximately 5 µs. In contrast, the minimal PTA duration was about 420 µs, ensuring sufficient temporal coverage and information content.

To further extend coverage, downsampling factors of 2, 4, 8, and 16 were applied. To incorporate signals from all four detectors, multiple input combinations were evaluated, ranging from single-detector inputs (A) to three-detector groupings (B–C–D). Grayscale tensors, obtained by averaging detector signals, were also tested. In total, 168 configurations were analyzed. The number of PTAs varied with the applied downsampling.

Training and testing were performed on an NVIDIA RTX GPU (12 GB memory) using the TensorFlow framework. Due to memory constraints, PTAs were processed in micro-batches of 10,000. Approximately 10% of the dataset was reserved for validation, and test data were separated prior to training. For each detector combination and downsampling factor, four CNN models were trained and evaluated. Separate models were created for each input configuration.

The classification task employed convolutional neural networks implemented in TensorFlow / Keras.

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Input data consisted of RGB images with a fixed size of 256×256 pixels; no additional resizing was performed during loading. The model architecture comprised three convolutional layers (32, 64, and 128 filters, kernel size 3 × 3, ReLU activation, and max pooling after each layer), followed by a flattening layer and a dense layer with 128 units (ReLU activation) [123]. The output layer consisted of three neurons with softmax activation to classify images into three categories (**c5** (Cm = 5%, SMDp = 18.7μm) , **c10** (Cm = 10%, SMDp = 18.7μm), **c20** (Cm = 10%, SMDp = 18.7μm) for Cm; **a5** (Cm = 5%, SMDp = 9.4μm), **b5** (Cm=5%, SMDp = 4.0μm), **c5** (Cm = 5%, SMDp = 18.7μm) for SMDp). The model used the Adam optimizer, sparse categorical cross-entropy loss, and tracked accuracy. Training was performed in batches to optimize GPU memory usage. The dataset was organized in labeled folders, with labels extracted from filenames using regular expressions. All training histories, model weights, and evaluation results were stored for reproducibility.

This work primarily focused on demonstrating the feasibility of combining PTA-based representations with AI models. With available hardware, maximal architecture was implemented to achieve sufficient validation accuracy. Further optimization of model design, training strategies, and PTA quality, such as resolution and size, is expected to significantly improve predictive performance.

4. Results

The dataset corresponding to this study, including PTAs with different detector combinations, trained AI models, Python scripts for training and validation, and CSV files with results, is available in [29]. In this section, only a representative portion of the results are presented and discussed. Figures 1 and 2 illustrate the prediction performance of the AI models for different detector configurations, starting with PTAs from a single detector (A) and extending to PTAs from three detectors (B–C–D). Figure 1 shows the prediction error of PTA-based classification of mass concentration (**Cm**). Two downsampling factors are compared: 1 (419μs) and 16 (13.4ms). A PTA with downsampling factor 16 therefore covers approximately 16 times more light-scattering signals from individual coal monoethylene glycol slurry droplets. Additionally, RGB and grayscale modes were compared. A similar graphical representation was generated for the classification of the mean particle size (**SMDp**) of the coal particles suspended in the slurry.

Overall, the prediction of Cm is significantly more reliable than that of SMDp. This may be explained by the fact that average particle sizes overlap strongly across samples a5, b5, and c5, making it difficult for the AI to distinguish between them. In particular, detector C produced the poorest results, as did the combinations A–C and A–D. Consequently, the

SMDp predictions at downsampling factor 1 are not meaningful for further discussion. Nevertheless, it is evident that increasing the downsampling—and thus extending the PTA time interval—can improve classification results. This effect can be attributed to the fact that a longer PTA contains more scattering signals from droplets, allowing the AI to perform a better averaging. This trend holds true for both **Cm** and **SMDp** prediction.

Figure 1 also shows that at downsampling factor 1, RGB mode clearly outperforms grayscale mode. The reason is that CNNs require information about relative shifts between detector signals for accurate classification. Grayscale representation eliminates these shifts by averaging signals into a single channel, thereby reducing information content. For single-detector PTAs (A, B, C, D), this averaging has no effect, as only one signal is available.

Surprisingly, the results indicate that the number of detector channels becomes less important as the downsampling factor increases. This was unexpected and is currently under further investigation. If confirmed, this finding would suggest that the proposed approach could be applied to TSTOF instruments even when only a single detector is active. Using AI with single-detector signals and the associated benefits has also been reported in [30].

5. Conclusion

The use of PTAs in combination with AI opens new diagnostic possibilities for investigating complex sprays and particle-laden flows. Potential applications include determining droplet size and velocity distributions, estimating refractive indices of multicomponent liquids, quantifying solid loading in suspension sprays, monitoring pigment distribution in paint sprays, and enabling real-time diagnostics in industrial atomization and coating processes. Overall, the results presented here show that the Particle-Tensor-AI approach, even at its early stage of development, delivers promising performance and holds strong potential for advanced spray diagnostics. A comprehensive review of spray diagnostics, including PDA [23, 24], TSTOF, and other advanced techniques, is provided by Tropea in [31], where their limitations and challenges are discussed.

Declaration of Competing Interest

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

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