

Real-World Application of Low-Cost PM Sensors in Dedusting Systems

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Preamble

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Zusammenfassung

Luftschadstoffe wirken sich nachteilig auf die menschliche Gesundheit und die Umwelt aus. Sie entstehen sowohl aus natürlichen Quellen als auch aus anthropogenen Prozessen, insbesondere bei Verbrennungsvorgängen in der Energieversorgung, im Haushalt und im Verkehr sowie in der Landwirtschaft und der Industrie. Um lokal emittierte Partikeln aus der Prozessluft abzutrennen, kommen in zahlreichen industriellen Anwendungen Entstaubungsanlagen wie Abreinigungsfilter und Nassabscheider zum Einsatz. Vor dem Hintergrund steigender Energiekosten beeinflusst nicht nur die Minimierung der Partikelemissionen, sondern auch der spezifische Energiebedarf dieser Anlagen maßgeblich deren wirtschaftliche Bewertung. Gleichzeitig führen variierende Prozessparameter zu wechselnden Absaugbedingungen, was flexible Entstaubungslösungen erforderlich macht. Modulare Anlagenkonzepte können diese Flexibilität gewährleisten. Ergänzend ermöglicht eine modellgestützte Prozesssimulation auf Basis empirischer Berechnungsgleichungen aus der Literatur die Vorausberechnung von Abscheidegraden und Leistungsaufnahmen. Für eine verlässliche Modellvalidierung von Emissionen sind jedoch kontinuierliche und belastbare Emissionsdaten erforderlich. Low-Cost Particulate Matter Sensoren (LC-PM-Sensoren) bieten hierfür ein großes Potenzial, da sie kompakt, kostengünstig und prinzipiell geeignet für eine prozessintegrierte Inlineüberwachung sind. Ihre quantitative Einsetzbarkeit unter hohen Staubkonzentrationen und variablen Betriebsbedingungen ist jedoch bisher nur unzureichend untersucht. Die vorliegende Arbeit bewertet daher die Eignung eines solchen LC-PM-Sensors (Sensirion SPS30), zur Messung von Partikelanzahlkonzentrationen und Partikelgrößenverteilungen in Absauganlagen. Die Untersuchungen erfolgen in drei Schritten. Zunächst werden Laborstudien unter idealisierten Bedingungen durchgeführt, um die LC-PM-Sensoren mit

etablierter Referenzmesstechnik (RI) (Palas Promo 2000H mit welas2100HP) zu vergleichen und systematische Abweichungen zu quantifizieren. Anschließend erfolgt der Einsatz in Entstaubungsanlagen. Im ersten Anwendungsfall werden die Sensoren in einem Nassabscheider installiert, um kontinuierlich Partikelanzahlkonzentrationen und Größenverteilungen zu erfassen. Im zweiten Anwendungsfall werden sie in einem Patronenfiltersystem integriert, um zu prüfen, inwieweit die Sensoren die modellgestützte Vorausberechnung von Emissionen unterstützen können.

Fünf LC-PM-Sensoren wurden parallel zu einem RI bei relativen Feuchten von 55 % und 95 % unter idealisierten Bedingungen in einer Messkammer untersucht. Bei beiden Feuchtebedingungen folgte die Abweichung zwischen den LC-PM-Sensoren und RI-Messungen demselben konzentrationsabhängigen Verlauf. Für das verwendete Partikelsystem wurde kein Einfluss der relativen Feuchte auf diese Abweichung festgestellt. Bis zu Partikelanzahlkonzentrationen von etwa $6 \times 10^4 \text{ l/cm}^3$ konnte die Abweichung zwischen den LC-PM-Sensoren und dem RI durch eine Polynomfunktion dritter Ordnung mit sensorspezifischen Koeffizienten beschrieben werden. Der Vergleich der fünf LC-PM-Sensoren zeigte nur geringe Unterschiede innerhalb des Sensorarrays. Die mittlere relative Standardabweichung änderte sich von 5.75 % bei 55 % relativer Feuchte auf 5.95 % bei 95 % relativer Feuchte. Die mittlere absolute relative Abweichung änderte sich von 4.25 % auf 4.46 %. LC-PM-Sensor 1 wich konsistent von den übrigen Sensoren ab. Möglicherweise aufgrund des abweichenden Produktionsdatums. Neben der Partikelanzahlkonzentration bildeten die LC-PM-Sensoren auch die vom RI gemessenen Partikelgrößenverteilungen und deren zeitliche Entwicklung bei beiden Feuchteniveaus ab. Die stärksten Verschiebungen der Partikelgrößenverteilung traten bei hoher relativer Feuchte im Größenbereich von etwa $0.3 \mu\text{m}$ bis $0.7 \mu\text{m}$ auf. Die LC-PM-Sensoren bildeten außerdem die Verläufe der Fraktionen $\Delta\text{PC}_{\text{N,PM}_{0.5}}$, $\Delta\text{PC}_{\text{N,PM}_{1.0}}$ und $\Delta\text{PC}_{\text{N,PM}_{2.5}}$ ab. Auf dieser Grundlage wurde der Korrekturfaktor α_1 für die gesamte Partikelanzahlkonzentration sowie die Korrekturfaktoren $\alpha_{2,i}$ für die einzelnen Größenklassen der Partikelgrößenverteilung entwickelt. Da beide sensorspezifische Unterschiede zeigten, wurden sie für jeden Sensor separat bestimmt. In Kombination ermöglichten diese Faktoren die Korrektur der gesamten Partikelanzahlkonzentration und der Partikelgrößenverteilung. Die Ergebnisse zeigen, dass die untersuchten LC-PM-Sensoren unter den untersuchten kontrollierten Bedingungen zur Messung der Partikelanzahlkonzentration und der Partikelgrößenverteilung eingesetzt werden können, sofern

eine sensorspezifische Korrektur angewendet wird.

Nach den Labormessungen wurden die LC-PM-Sensoren an zwei Positionen im Versuchsstand eines Nassabscheider installiert. Im Rohgaskanal unterschätzte der installierte LC-PM-Sensor 2 die Partikelanzahlkonzentration und erfasste etwa $6.4 \times 10^4 \text{ 1/cm}^3$ gegenüber $8.9 \times 10^4 \text{ 1/cm}^3$, die mit dem RI gemessen wurden. Die Gesamtpartikelanzahlkonzentration lag oberhalb des Bereichs, der zur Herleitung der Polynomkorrektur dritter Ordnung verwendet wurde. Die Extrapolation über deren Obergrenze von etwa $4 \times 10^4 \text{ 1/cm}^3$ hinaus führte nach der Korrektur zu einer Überschätzung. An der zweiten Messposition oberhalb des Tropfenabscheiders im Nassabscheider maßen vier LC-PM-Sensoren (1, 3, 4 und 5) Partikelanzahlkonzentrationen innerhalb des Gültigkeitsbereichs der Korrekturfunktion. Ihre Abweichungen vom Referenzinstrument lagen zwischen 34 und 48% und sanken nach Anwendung der Polynomkorrektur auf 1 bis 20%. Die erweiterte Auswertung der Messungen im Nassabscheider zeigte außerdem, dass die LC-PM-Sensoren lokale Konzentrationsverläufe über alle untersuchten Partikelgrößenklassen hinweg abbildeten, auch bei Betrieb oberhalb ihrer nominalen Grenzwerte. Vor Anwendung der Skalierungsfaktoren α_1 und $\alpha_{2,i}$ bildeten die meisten Sensoren die Fraktion $\Delta PC_{N,PM_{0.5}}$ ab, während LC-PM-Sensor 3 sie unterschätzte. Im Vergleich zur Messkammer wurde im Nassabscheider ein höherer Anteil submikroner Partikel infolge der Abscheidung größerer Partikeln beobachtet. Dadurch überschritten die Konzentrationen von $\Delta PC_{N,PM_{0.5}}$ den spezifizierten Maximalwert von 3000 1/cm^3 um eine Größenordnung. Die Fraktion $\Delta PC_{N,PM_{1.0}}$ wurde im Allgemeinen unterschätzt, während $\Delta PC_{N,PM_{2.5}}$ von den LC-PM-Sensoren 3 und 5 überschätzt wurde. Nach Anwendung der Skalierungsfaktoren überschätzten alle Sensoren die Fraktion $\Delta PC_{N,PM_{0.5}}$, stimmten jedoch für $\Delta PC_{N,PM_{1.0}}$ besser mit dem Referenzinstrument überein. Für $\Delta PC_{N,PM_{2.5}}$ verschoben sich alle LC-PM-Sensoren zu kleineren Werten, wodurch sich die Übereinstimmung mit dem Referenzinstrument verbesserte.

Im letzten Schritt erfolgte die Integration von LC-PM-Sensoren in ein Patronenfiltersystem. Dabei wurde untersucht, ob sich gemessene Emissionsdaten für den Vergleich mit Modellgleichungen des Systems und zur Ableitung von Betriebszuständen nutzen lassen. Die verwendeten Sensoren wurden nicht durch sensorindividuelle Korrekturfunktionen angepasst, um ihre Einsetzbarkeit im untersuchten System ohne vorherige Anpassung zu prüfen. Die Bewertung stützte sich auf Modellgleichungen, die aus empirischen Korrelationen der Lite-

ratur abgeleitet wurden und das Emissionsverhalten sowie den Leistungsbedarf in Abhängigkeit von den Betriebsparametern beschreiben. Die Messungen der LC-PM-Sensoren wurden anschließend genutzt, um die emissionsbezogenen Anteile dieser Modellgleichungen durch den Vergleich gemessener Emissionsverläufe mit den zugehörigen Modellvorhersagen anzupassen und zu prüfen. Die Ergebnisse zeigten, dass LC-PM-Sensoren verwendet werden können, um Emissionstrends des untersuchten Filtersystems zu erfassen und die Messdaten mit den zugehörigen Modellvorhersagen zu vergleichen. Trotz ihres begrenzten Spezifikationsbereichs lieferten die Sensoren Emissionsmessungen mit ausreichender zeitlicher Auflösung, um charakteristische Filtrationsverläufe zu identifizieren und modellbasierte Vorhersagen zu unterstützen. Der Vergleich zwischen modellierten und experimentell bestimmten Betriebspunkten ergab für den vorhergesagten Leistungsbedarf bei allen untersuchten Betriebsbedingungen Abweichungen von unter 20 %. Dies zeigte, dass die Modellgleichungen für Druckverlust und Regenerationsenergie die gemessenen Zusammenhänge des Systems abbildeten. Die Abweichungen zwischen modellierten und gemessenen Emissionen lagen bei einem eintragsseitigen Staubmassenstrom von etwa 500 g/h bei bis zu 70% und bei etwa 2800 g/h bei bis zu 800%. Diese Abweichungen ergaben sich unter anderem aus dem Einfluss von $E_{\min}$ auf die berechneten Emissionen. Die Messungen der LC-PM-Sensoren bildeten qualitative Emissionsmuster und charakteristische Peakstrukturen innerhalb der Filtrationszyklen ab.

Insgesamt zeigte diese Untersuchung, dass LC-PM-Sensoren für die Überwachung des Emissionsverhaltens in Entstaubungssystemen eingesetzt werden können und zur Prüfung und Weiterentwicklung empirischer Modellgleichungen beitragen. Zusammenfassend zeigt diese Arbeit, dass die in dieser Arbeit verwendeten LC-PM-Sensoren robuste qualitative und semi-quantitative Informationen liefern und ihren nutzbaren Messbereich um mindestens eine Größenordnung erweitern. Damit eignen sie sich für die kontinuierliche Prozessüberwachung und die Entwicklung von Modellen zur Zustandsabbildung und Prozessoptimierung von Entstaubungssystemen. Weiterer Forschungsbedarf besteht hinsichtlich der Erfassung der Partikelgrößenverteilung unter realen Prozessbedingungen, der Langzeitstabilität, der Sensorkalibrierung für unterschiedliche Staubtypen sowie der automatisierten Integration von LC-PM-Sensordaten in adaptive digitale Modelle.

Abstract

Air pollutants have been shown to adversely affect human health and the environment. They arise from both natural sources and anthropogenic processes, in particular from combustion processes in energy supply, households, and transport, as well as from agriculture and industry. In many industrial applications, dedusting systems such as pulse-cleaned filters and wet separators are used to remove locally emitted particles from process air. Against the background of rising energy costs, not only the minimization of particle emissions but also the specific energy demand of these systems has a major influence on their economic evaluation. At the same time, varying process parameters lead to changing extraction conditions, which require flexible dedusting solutions. Modular system concepts can provide this flexibility. In addition, model-based process simulation using empirical calculation equations from the literature enables the prediction of separation efficiencies and power demand. Reliable model validation, however, requires continuous and robust emission data. Low-cost particulate matter sensors (LC-PM-Sensors) offer potential for this purpose, as they are compact, inexpensive, and in principle suitable for process-integrated inline monitoring. Their quantitative applicability at high dust concentrations and under varying operating conditions, however, has not yet been sufficiently investigated. The present work therefore evaluates the suitability of such a sensor (Sensirion SPS30) for the measurement of particle number concentrations and particle size distributions in extraction systems. The investigation was carried out in three steps. First, laboratory studies were conducted under idealized conditions in order to compare the LC-PM-Sensors with established reference instrumentation (RI) (Palas Promo 2000H with welas2100HP) and to quantify systematic deviations. This was followed by their application in dedusting systems. In the first application case, the sensors were

installed in a wet separator in order to continuously record particle number concentrations and particle size distributions. In the second application case, they were integrated into a cartridge filter system in order to examine to what extent the sensors can support the model-based prediction of emissions.

Five LC-PM-Sensors were examined in parallel with a RI at relative humidities of 55 % and 95 % in a measurement chamber under idealised conditions. At both humidity levels, the deviation between the LC-PM-Sensors and the RI measurements followed the same concentration trend. For the particle system used, no influence of relative humidity on this deviation was found. Up to particle number concentrations of approximately $6 \times 10^4 \text{ 1/cm}^3$, the deviation between the LC-PM-Sensors and the RI could be described by a third-order polynomial function with sensor-specific coefficients. Comparison of the five LC-PM-Sensors showed only small differences within the sensor array. The mean relative standard deviation changed from 5.75 % at 55 % relative humidity to 5.95 % at 95 %. The mean absolute relative deviation changed from 4.25 % to 4.46 %. LC-PM-Sensor 1 differed consistently from the other sensors, possibly due to its different production date. In addition to particle number concentration, the LC-PM-Sensors also reproduced the particle size distributions measured by the RI and their temporal evolution at both humidity levels. The strongest shifts in the particle size distribution occurred at high relative humidity in the size range from approximately $0.3 \mu\text{m}$ to $0.7 \mu\text{m}$. The LC-PM-Sensors also reproduced the trends of the $\Delta\text{PC}_{\text{N,PM}_{0.5}}$, $\Delta\text{PC}_{\text{N,PM}_{1.0}}$, and $\Delta\text{PC}_{\text{N,PM}_{2.5}}$ fractions. On this basis, the correction factor α_1 for the total particle number concentration and the correction factors $\alpha_{2,i}$ for the individual size classes of the particle size distribution were developed. In combination, these factors enabled correction of the total particle number concentration and the particle size distribution. The results show that the investigated LC-PM-Sensors can be used for the measurement of particle number concentration and particle size distribution under the investigated controlled conditions, provided that sensor-specific correction is applied.

After the laboratory measurements, the LC-PM-Sensors were installed at two positions in the wet separator test facility. In the raw-gas channel, the installed LC-PM-Sensor 2 underestimated the particle number concentration and recorded approximately $6.4 \times 10^4 \text{ 1/cm}^3$ compared with $8.9 \times 10^4 \text{ 1/cm}^3$ measured by the RI. The total particle number concentration was above the range used to derive the third-order polynomial correction. Extrapolation

beyond its upper limit of approximately $4 \times 10^4 \text{ 1/cm}^3$ led to overestimation after correction. At the second measurement position above the droplet separator in the wet separator, four LC-PM-Sensors (1, 3, 4, and 5) measured particle number concentrations within the validity range of the correction function. Their deviations from the reference instrument ranged from 34 to 48% and decreased to 1 to 20% after application of the polynomial correction. The extended evaluation of the measurements in the wet separator also showed that the LC-PM-Sensors reproduced local concentration trends across all examined particle size classes, including operation above their nominal limits. Before application of the scaling factors α_1 and $\alpha_{2,i}$, most sensors reproduced the $\Delta PC_{N,PM_{0.5}}$ fraction, whereas LC-PM-Sensor 3 underestimated it. Compared with the measurement chamber, a higher proportion of submicron particles was observed in the wet separator, due to the separation of larger particles within the wet separator. As a result, the concentrations of $\Delta PC_{N,PM_{0.5}}$ exceeded the specified maximum value of 3000 1/cm^3 by one order of magnitude. The $\Delta PC_{N,PM_{1.0}}$ fraction was generally underestimated, whereas $\Delta PC_{N,PM_{2.5}}$ was overestimated by LC-PM-Sensors 3 and 5. After application of the scaling factors, all sensors overestimated the $\Delta PC_{N,PM_{0.5}}$ fraction but showed better agreement with the RI for $\Delta PC_{N,PM_{1.0}}$. For $\Delta PC_{N,PM_{2.5}}$, all LC-PM-Sensors shifted toward lower values, which improved agreement with the RI.

In the final step, LC-PM-Sensors were integrated into a cartridge filter system. The aim was to examine whether measured emission data can be used for comparison with model equations of the system and for the derivation of operating states. The sensors used were not adjusted by sensor-specific correction functions, in order to assess their applicability in the investigated system without prior adjustment. The evaluation was based on model equations derived from empirical correlations in the literature, which describe emission behavior and power demand as functions of the operating parameters. The measurements of the LC-PM-Sensors were then used to adjust and examine the emission-related parts of these model equations by comparing measured emission profiles with the corresponding model predictions. The results showed that LC-PM-Sensors can be used to capture emission trends of the investigated filter system and to compare the measured data with the corresponding model predictions. Despite their limited specification range, the sensors provided emission measurements with sufficient temporal resolution to identify characteristic filtration patterns and to support model-based predictions. The comparison between modeled and experimentally determined operating

points showed deviations below 20% for the predicted power demand under all investigated operating conditions. This showed that the model equations for pressure loss and regeneration energy reproduced the measured dependencies of the system. The deviations between modeled and measured emissions were up to 70% at an inlet dust mass flow rate of approximately 500 g/h and up to 800% at approximately 2800 g/h. These deviations resulted in part from the influence of $E_{\min}$ on the calculated emissions. The measurements of the LC-PM-Sensors reproduced qualitative emission patterns and characteristic peak structures within the filtration cycles. Overall, this investigation showed that LC-PM-Sensors can be used for monitoring the emission behavior of dedusting systems and can contribute to the examination and further development of empirical model equations.

In summary, this work shows that the LC-PM-Sensors used in this study provide robust qualitative and semi-quantitative information and extend their usable measurement range by at least one order of magnitude. They are therefore suitable for continuous process monitoring and for the development of model-based approaches for dedusting systems. Further research is required with regard to the measurement of particle size distributions under real process conditions, long-term stability, the sensor calibration for different dust types, and the automated integration of LC-PM-Sensor data into adaptive digital models.

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1

Introduction

Air pollutants adversely affect human health and the environment. In addition to natural sources, combustion processes (power generation, residential heating, transportation), agriculture, and industry are major contributors.[1] Among these pollutants, particulate matter in the $PM_{2.5}$ and PM_{10} fractions is considered particularly harmful, alongside ozone and nitrogen oxides. Elevated concentrations of $PM_{2.5}$ and PM_{10} are causally linked to respiratory and cardiovascular diseases, lung cancer, and increased mortality [1–3]. To mitigate locally generated particulate emissions from industrial processes, industrial practice employs a wide range of dust collection systems, including cartridge filters that provide large filtration area within compact plant dimension and wet separators, whose operating parameters such as the liquid-to-air ratio significantly affect pressure loss and dust emissions during exhaust-gas cleaning of processes like welding [4]. Given rising energy costs, both low emissions and low pressure loss are decisive for the economic assessment of these systems [5–8]. Frequent changes in processed materials and operating parameters further demand flexible, modular system concepts (e.g., cartridge filter units with optional pre-separators). Model-based representations of such modules can support the preliminary assessment of collection efficiency and energy demand based on empirical correlations from the literature, provided that these models are validated against experimental data. Continuous, process-relevant particulate monitoring is essential for optimizing separation efficiency and energy use in industrial dedusting. [9, 10] While cost-effective differential

pressure sensors are widely used to track pressure loss, continuous monitoring of particulate emissions remains uncommon. Low-cost particulate-matter sensors (LC-PM-Sensors) offer a promising route to close this gap, provided their suitability under process conditions is demonstrated. Beyond emission compliance, cost-effective characterization of aerosol properties (particle number concentration (PNC) and particle size distribution (PSD)) is critical for robust process control and the operation of separation processes [11, 12].

The potential of LC-PM-Sensors has been widely explored for ambient air-quality applications [13–15], including sensor networks [16–18], calibration strategies [19–21], and integration with meteorological data [22–24]. More recently, several studies have investigated their use in industrial dust processes for continuous monitoring and diagnostics [25–31]. Table 1.1 presents a comprehensive overview of selected significant studies on the utilisation of LC-PM-Sensors for emission measurement, showcasing the specific sensors employed, such as the SDS011, SPS30, and OPC-N3, their applications, the primary results attained and the comparative systems referenced in these studies. The studies consistently show that these sensors can reproduce trends observed with established reference systems or identify characteristic emission patterns across different operating conditions. In particular, the results indicate that LC-PM-Sensors are able to detect and characterize emission behaviors, including emission peaks and localized particle concentration hotspots, with notable reliability. This is evident in applications such as filter monitoring and the detection of leaks in baghouse filters, where the sensors have provided valuable qualitative insights into particulate emissions.[26] These findings highlight the potential of LC-PM-Sensors as cost-effective tools for emission monitoring in both research and industrial settings. The subsequent step is therefore to examine their suitability for quantitative particle concentration measurements in real dedusting systems, with the aim of obtaining accurate data that may support future process control strategies. Most low-cost optical particle counters directly report PNC by size bins but derive mass concentrations using conversion factors tuned to ambient aerosols. Under process aerosols, where refractive index, morphology, and effective density deviate from those assumptions, mass estimates become biased. Accordingly, the evaluation of sensor behavior in this work is mainly based on PNC. In Chapter 4, mass concentration is used instead, as the model equations are formulated in terms of mass-related quantities. Also, the LC-PM-Sensors data were not adjusted by sensor-specific corrections functions, in order to assess their applicability in the investigated system without prior adjustment.

Table 1.1: Summary of Studies on LC-PM-Sensors for Emission Measurements. [32]

Study	Sensor	Application	Main Results	Comparison System
[25]	SDS011 (Nova Fitness)	Filter emission measurements	SDS011 showed the same trend as the reference system and responded promptly to particle concentration changes in the chamber.	Palas [®] Promo [®] 2000 with welas [®] 2100
[26]	SPS30 (Sensorion)	Pulse-jet filter emissions	SPS30 qualitatively showed PM emission behavior and identified three distinct emission levels for different filter media.	Palas [®] Promo [®] 2000 with welas [®] 2100
[28]	OPC-N3 (Alphasense)	Monitoring individual filter bags	Detected emission peaks after filter regeneration, correlating with overall emissions in a pilot-scale baghouse filter.	Palas [®] Promo [®] 2000 with welas [®] 2100
[27]	OPC-N3 (Alphasense)	Filter material and operation	Identified emission events from filter regeneration that correlated with total dust emissions under varying conditions.	Palas [®] Promo [®] 2000 with welas [®] 2100
[29]	OPC-N3 (Alphasense)	Emission hotspots	Successfully detected emission hotspots, such as leaks, in a small-scale baghouse filter using spatially distributed sensors.	Palas [®] Promo [®] 2000 with welas [®] 2100

The objective of Chapter 2 is to investigate the capability of LC-PM-Sensors (SPS30, Sensirion AG) to measure particle concentrations beyond their specified concentration range under controlled laboratory conditions. The focus lies on evaluating their suitability for subsequent integration into dedusting systems. The LC-PM-Sensors are compared against established particle measurement instruments used as reference technologies (Palas Promo 2000H equipped with a welas2100HP). The analysis considers both the total measured particle number concentration and the number concentration within the individual size classes of the LC-PM-Sensor to assess measurement quality with respect to particle number concentration and particle size distribution. Based on the simultaneous acquisition of LC-PM-Sensor data and reference measurements, correction functions derived to enable the determination of more representative emission values under elevated concentration conditions. These results form the foundation for evaluating the applicability of LC-PM-Sensors in dedusting systems and for refining their use in emission monitoring tasks.

In Chapter 3, the LC-PM-Sensors characterized in the previous section are implemented in a novel wet separator to evaluate their measurement performance during separator operation. While the laboratory experiments provided controlled conditions with defined particle concentrations, particle size distributions, and elevated relative humidity, the wet scrubber environment was characterized by elevated relative humidity as well as additional influencing factors such as fluctuating dust concentrations and varying local gas velocities. These conditions reflect the operating conditions in the wet scrubber and thus provide a basis for assessing the use of LC-PM-Sensors for process-integrated particle monitoring. The objective of this work is to determine whether the corrected LC-PM-Sensors data are capable of detecting local particle number concentrations, particle size distributions, and spatial or temporal concentration fluctuations within the wet scrubber. The ability to resolve such local variations is essential for generating process relevant information. LC-PM-Sensor measurements are compared with data obtained from the established particle reference instrumentation previously used during the calibration phase. This comparison allows an evaluation of the extent to which the calibration derived under laboratory conditions remains valid in a wet separation process and whether LC-PM-Sensors can serve as suitable tools for in-line monitoring of particle-related process parameters.

In Chapter 4, the suitability of LC-PM-Sensors for use in a pulse-jet-cleaned cartridge filter system is assessed with the aim of extracting operational infor-

mation from measured emission data. The focus lies on determining whether LC-PM-Sensors provide the temporal and quantitative resolution required to monitor and evaluate the operating state of modular dedusting systems. In this investigation, no further calibration of the LC-PM-Sensors is performed and non corrected mass based particle concentrations are used, as the objective is limited to demonstrating their fundamental applicability in industrial settings. The analysis is based on model equations derived from empirical correlations available in the literature. These model equations provide an initial description of emission behavior and power demand as functions of relevant operating parameters. They serve as a framework for predicting operating states and identifying energy and emission optimized operating conditions. LC-PM-Sensor measurements are subsequently used to adjust and validate the emission related components of these model equations. Emission profiles of individual filtration cycles are compared with the corresponding model predictions to quantify deviations and assess model accuracy. This approach enables an evaluation of the extent to which LC-PM-Sensors can contribute to process monitoring, model refinement, and predictive operation of dedusting systems. In Chapter 5, a summary of the findings of this work is presented, followed by an outlook on future research activities.

2

Low-Cost PM-Sensors for Emission Characterisation

This chapter investigates the capability of LC-PM-Sensors to measure particle emissions beyond their specified concentration range under controlled laboratory conditions. The focus lies on assessing their suitability for subsequent integration into industrial dust collection systems. Such an evaluation is required because particle concentrations in dust collection systems exceed $3 \times 10^3 \text{ l/cm}^3$. Preliminary studies indicate that the sensors can qualitatively detect concentrations above their specified range.[\[26\]](#) Controlled laboratory experiments enable a systematic assessment of measurement deviations under ideal conditions prior to industrial application. The LC-PM-Sensors are compared against established particle measurement instrumentation used as reference technology. The analysis considers both the total measured particle number concentration and the number concentration within the individual size classes of the LC-PM-Sensor to evaluate measurement quality with respect to particle number concentration and particle size distribution. The influence of relative humidity on measurement deviation is also investigated. Based on the simultaneous measurement of LC-PM-Sensor data and reference measurements, correction curves can be derived to enable the determination of more representative emission values under elevated concentration conditions. These results form the basis for evaluating the applicability of LC-PM-Sensors in industrial environments and for refining their use in emission monitoring tasks.

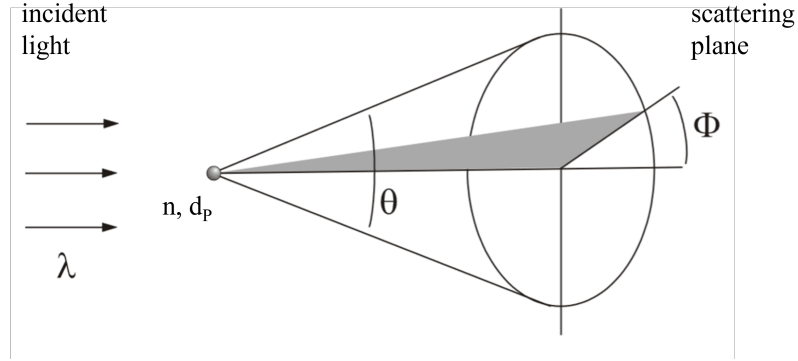


Figure 2.1: Schematic representation of the scattering of a light wave by a particle. Here, λ denotes the wavelength of the incident light, n the refractive index, d_p the particle diameter, θ the detection angle of scattered light, and ϕ the polarization angle of the scattered wave. According to [4].

2.1 Measurement Basics

For the online measurement of particle concentrations in a gas flow, optical methods are utilized, among others. These methods can be classified into imaging methods and scattered light methods. Since the particle measurement technique employed within this study exclusively relies on scattered light, only this method is discussed in detail below.

The measurement principle of scattered light techniques is based on the scattering of a light wave with wavelength λ on a spherical particle of diameter d and refractive index n . Due to diffraction, reflection, and refraction, a directional change in the propagation of light occurs [33]. Figure 2.1 illustrates schematically the scattering of light by a single particle. Additionally, the scattering angle θ and the polarization angle ϕ are indicated [34]. As shown in Figure 2.1, the scattering effects of light depend on the properties of the particles, the wavelength of the light, their relative proportions, and the scattering angle between the observer and the illumination direction. To describe the relationship between particle size and wavelength, a scattering parameter α is introduced:

$$\alpha = \frac{\pi \cdot d}{\lambda} \quad (2.1)$$

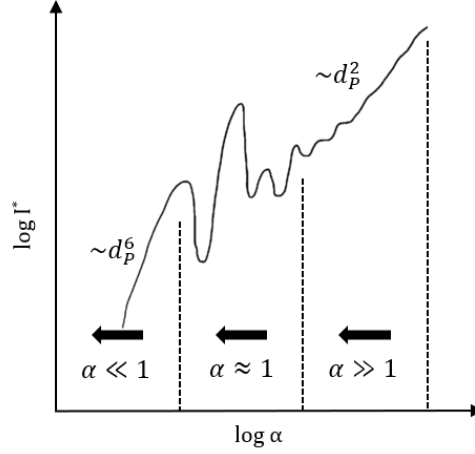


Figure 2.2: Schematic representation of the relationship between scattered light intensity and the size parameter α . Additionally, the three distinct scattering regimes ($\alpha \ll 1$, $\alpha \approx 1$, $\alpha \gg 1$) and their respective proportionalities to particle diameter are indicated. According to [35].

Consequently, the intensity I of the light scattered by a single particle is derived from the intensity I_0 of the incident light on the particle, the polarization angle, detection angle, refractive index n , and scattering parameter α . The relative scattered light intensity I^* is thus expressed as:

$$I^* = \frac{I}{I_0} = f(\phi, \theta, n, \alpha). \quad (2.2)$$

Using the scattering parameter α , theoretical approaches for describing the particle size and angle dependency of scattered light intensity can be subdivided into the following three regions [35]:

- $\alpha \ll 1$: Rayleigh region
- $\alpha \approx 1$: Mie region
- $\alpha \gg 1$: Fraunhofer region

Figure 2.2 shows the relative scattered light intensity I^* plotted against the scattering parameter α for monochromatic light at a fixed scattering angle, presenting the different regions of the scattering parameter α . As illustrated in Figure 2.2, the relative scattered light intensity in the Rayleigh region ($\alpha \ll 1$)

depends on the particle diameter to the sixth power. In the geometrical optics region ($\alpha \gg 1$), a quadratic relationship between scattered light intensity and particle diameter exists. In the Mie region ($\alpha \approx 1$), pronounced fluctuations are evident, and an unambiguous assignment of scattered light intensity to particle size is generally not possible. This implies that, in measurement applications, more than one particle size can correspond to a single measured light intensity. For particle measurement in the Mie region, the use of white light with a 90° scattered light detection can smooth the intensity curve, thereby allowing a unique relationship between measured relative scattered light intensity and particle size. Alternatively, employing monochromatic light with 90° scattered light detection combined with an approximation function can yield an approximate relationship. [36]

To determine particle size using scattered light methods, reflection and refraction of waves upon encountering an interface are relevant. This behavior is described by the refractive index n , which consists of a real and an imaginary component. The real part predominantly determines light scattering, while the imaginary part describes reflective behavior. Assuming that reflection behavior can be neglected for the substances investigated, the refractive index is expressed as the ratio of the speed of light in a vacuum c to the speed of light in the particle v_p :

$$n = \frac{c}{v_p}. \quad (2.3)$$

2.2 Materials and Methods¹

2.2.1 Aerosol Measurement Technology

In this work, two distinct types of optical particle counters were employed for comparison. The first instrument used was a SPS30 from Sensirion AG (LC-PM-Sensor). The second was a state-of-the art precision laboratory Palas Promo 2000H aerosol spectrometer equipped with a welas 2070HP sensor (RI) and a welas 2100HP sensor (RI) (see Figure 2.3). The RIs were employed as reference measurement devices for the validation of the measured particle concentration and particle size distribution of the LC-PM-Sensor in different ranges of particle concentrations. A detailed account of the specifications of the sensors can be found in Table 2.1.

¹Parts of this Chapter are published in Reinke et al. [32].

Table 2.1: LC-PM-Sensor and RI specifications. Adapted from [32].

Device	LC-PM-Sensor - SPS30	RI - Promo 2000H & welas 2100HP
Manufacturer	Sensirion AG	Palas
Measured metrics	Number concentration: PM _{0.5} , PM _{1.0} , PM _{2.5} Mass concentration: PM _{1.0} , PM _{2.5}	Mass and number concentration, particle size distributions
Calculated values	PM ₄ , PM ₁₀ (number and mass concentration)	Size-resolved PM _x conversion
Detectable particle size range	0.3 µm to 2.5 µm	0.2 µm to 10 µm; 0.3 µm to 17 µm; 0.6 µm to 40 µm (user selectable)
Particle size categorization	5 bins (schematic representation see Figure 2.10)	32 bins (schematic representation see Figure 2.10)
Maximum concentration (number based)	3000 1/cm ³	5 × 10 ⁵ 1/cm ³ (2100) 1 × 10 ⁶ 1/cm ³ (2070)
Light source	Monochromatic Laser (λ ≈ 600 nm)	White light (Xenon arc lamp)
Approx. cost	≈ 100 €	> 30.000 €
Dimensions (L x W x H) / mm	40 x 40 x 12	245 x 100 x 80
Response time	≈ 1 s	≈ 1 s
Volume flow	Not known	5 L/min
Configuration	Not known	ρ _{particle} = 2700 kg/m ³ , n = 1.59, spherical particles

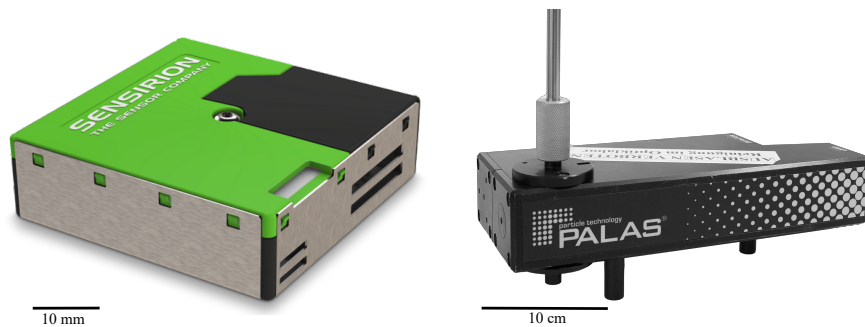


Figure 2.3: Representation of the LC-PM-Sensor SPS30 from Sensirion AG (left) and the RI from Palas GmbH (right). [32]

2.2.1.1 Reference Instrument (Palas Promo 2000H with welas 2070HP/2100HP)

The RIs are aerosol spectrometers that operate on the basis of the physical measurement principle of light scattering by a single particle. A detailed description of the measurement principle is provided in [37]. Such instruments permit calculation of the concentration of particles and the related particle size distribution of those particles present in the aerosol. The particle density and optical properties (refractive index) can be considered when evaluating the measurement data. To prevent condensation of the aerosol within the measurement volume of the sensor, the aerosol channel can be heated. The aerosol channel was heated when the relative humidity was above environmental conditions. The two reference sensors differ in their respective measurement volumes (measurement volume welas2070HP « welas2100HP), which consequently result in differing maximum measurable particle concentrations (see Table 2.1). The RI operates at a sampling flow rate of 5 L/min.

2.2.1.2 Low-Cost Particulate-Matter Sensor (Sensirion SPS30)

The LC-PM-Sensor is designed for ambient particulate matter measurements and can be classified as a scattered-light aerosol spectrometer. The SPS30 operates on the principle of optical particle detection by laser light scattering. Ambient air is actively drawn through an internal measurement chamber by an integrated fan. As airborne particles pass through the illuminated detection volume, they scatter the incident laser light, and the resulting scattered light is detected by a photodetector. Based on the measured scattering intensity, the sensor derives particle number concentrations and estimates particle mass con-

centrations using internal calibration and signal processing algorithms. However, compared with the RI, the LC-PM-Sensor provides a smaller detectable size range, a lower particle size resolution, and a lower maximum measurable concentration, as summarized in Table 2.1. The following section presents the fundamental differences between the LC-PM-Sensor and RI. Since the scattered-light signal depends not only on particle size but also on particle properties such as refractive index, shape, and density, the measured particle concentration is subject to material-specific deviations. In the LC-PM-Sensor, these effects cannot be explicitly corrected during post-processing. In addition, coincidence effects and border zone errors are not accounted for [26]. By contrast, RIs can compensate for coincidence errors by incorporating the corresponding effect into the effective measurement time, thereby informing the user when particle concentrations exceed the acceptable coincidence threshold. Furthermore, RIs can reduce border zone errors by means of a T-shaped aperture [38]. Another relevant aspect affecting the measurement quality of the LC-PM-Sensor in comparison with RIs is the detectable particle size range. The LC-PM-Sensor detects particles in the optical size range of 0.3 μm to 2.5 μm . The fractions $\text{PM}_{1.0}$ and $\text{PM}_{2.5}$ are derived directly from measured particle events, whereas PM_4 and PM_{10} are estimated on the basis of typical aerosol profiles. In contrast, the RI is capable of measuring particle sizes up to 40 μm , depending on the selected user settings. It should also be noted that the flow rate of the LC-PM-Sensor cannot be adjusted, which may result in unrepresentative probe sampling under certain conditions. RIs address this limitation by allowing the use of application-specific sampling probe tips for different flow conditions. However, Gail and Gommel et al. [36] demonstrated that anisokinetic probe sampling has a negligible effect on particle measurements within and below the $\text{PM}_{2.5}$ fraction. According to the manufacturer, the maximum measurable particle concentration is 3000 $1/\text{cm}^3$ [39].

2.2.2 Test Dust and Particle Dispersing

The test dust is composed of limestone, which is a natural calcium carbonate [40]. The particle refractive index is $n_{\text{particle}} = 1.59$ and the particle density $\rho_{\text{particle}} = 2.7 \text{ g/cm}^3$. The mass based median value of the particle system is $x_{50,3} = 0.9 \mu\text{m}$. [40] The utilisation of the test dust ensures the presence of a considerable quantity of sub-micron particles.

The generation of the aerosol is achieved through the utilisation of a dust feeder, specifically a rotating brush disperser (NDF100-BD, FilTEq). The opera-

tional principle of the disperser is as follows: The particle system is supplied at a constant rate to a rotating brush by a spindle. The rotating brush continuously removes the powder plug generated by the spindle, depositing it in thin layers. Subsequently, the feed dust is expelled from the fibres of the brush and dispersed in the purge air stream. The resulting particle mass flow can be modified by modifying the rate of feed to the spindle. The resulting mass flow rate depends on both the properties of the particle material and the applied operating parameters. For the selected test dust, it varies within a range of 80 g/h to 150 g/h. [41, 42]

2.2.3 Measurement Chamber

In order to ascertain systematic discrepancies between individual LC-PM-Sensors and their deviation from the RI prior to installation within dedusting systems, the sensors are initially evaluated in a measurement chamber under adjustable and controlled environmental conditions. In addition to dry reference measurements, experiments were conducted under elevated relative humidity in order to assess sensor performance under moisture conditions comparable to those encountered in wet scrubber applications. Measurements at high relative humidity are relevant for several reasons. First, relative humidity influences light-scattering behavior even in the absence of particle deliquescence, due to changes in the optical properties of the surrounding medium and potential surface adsorption effects. Second, LC-PM-Sensors are inherently sensitive to ambient humidity since hygroscopic particle growth and water uptake increase light scattering, which can lead to an overestimation of particulate matter concentrations. [25] Third, industrial process environments frequently exhibit substantial and dynamic relative humidity variations. Consequently, the objective of these measurements is not to investigate the hygroscopic growth behavior of the test dust particles, but rather to quantify the humidity stability and robustness of the optical measurement system itself. The configuration of the measurement chamber is illustrated in Figure 2.4. The experimental setup comprises the following components: The initial component is the particle dispersing unit, which comprises a brush disperser (see Chapter 2.2.2). The second component is the measurement chamber, which has a volume of 1 m³. This chamber contains the particle sensors (RI and LC-PM-Sensors 1-5) and the humidity sensor, which is a testo 400 equipped with a robust humidity/temperature probe (Testo SE & Co. KGaA). The LC-PM-Sensors are linked to a personal computer via USB cables, enabling the recording of data at a 1 s interval. The RI

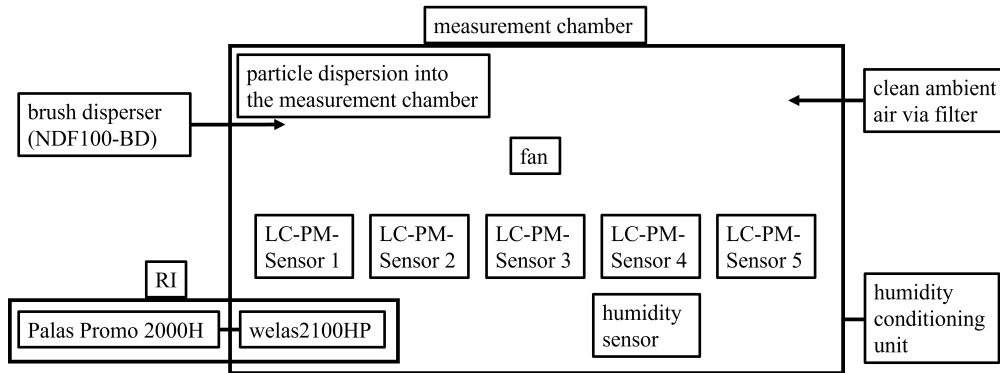


Figure 2.4: Schematic representation of the measurement chamber setup with a brush disperser, an internal fan, a humidity conditioning unit, LC-PM-Sensors, a RI and a humidity sensor. Adapted from [32]

records and saves data on a local hard drive, with a temporal resolution of 1 s. The sensors are installed at the same height. Furthermore, the measurement chamber is equipped with a fan. The fan ensures the homogeneous distribution of the dispersed particles within the chamber. Furthermore, the measurement chamber is linked to a humidity conditioning unit, to set the relative humidity within the chamber. The experiments were conducted in the following manner: Initially, the relative humidity was set at approximately 55 % at a temperature of 23 °C. Once a constant relative humidity had been established, particles were repeatedly injected (at a rate of 5 seconds each) until a particle number concentration of approximately $1 \times 10^5 \text{ l/cm}^3$ was reached at the RI. Once the required particle number concentration has been reached, the brush disperser is deactivated, and the subsequent decrease in particle number concentration is monitored using both the RI and LC-PM-Sensors. The reduction in particle concentration is attributable to the suction of the RI, which operates at a constant volume flow rate of 5 L/min, out of the measurement chamber. In order to compensate for pressure fluctuations, clean ambient air is introduced into the chamber via a filter. Once the particle number concentration, as measured by the RI, has fallen below approximately $1 \times 10^3 \text{ l/cm}^3$, the data recording is terminated. The aforementioned procedure is also applicable to the relative humidity condition of approximately 95 %. When measurements are conducted under conditions of elevated relative humidity, the RI is heated to a temperature of 80 °C in order to prevent condensation on the lenses of the sensor.

2.2.4 Data Preprocessing

To obtain and evaluate the dataset required for deriving the correction functions for particle number concentration and the correction scales for particle size distribution of the LC-PM-Sensors, experiments were conducted inside the measurement chamber under dry and humid conditions (see Chapter 2.2.3). The recorded RI and LC-PM-Sensor data were subsequently processed to ensure equidistant sampling and to correct for potential time delays. The RI data exhibits high fluctuations. The filtering procedure therefore had to reduce measurement noise while preserving relevant temporal concentration variations. For this purpose, a Savitzky Golay filter with a window size of 25 data points and a second order polynomial was applied to the RI data. The Savitzky Golay filter performs a local polynomial regression using the least squares method, thereby reducing high frequency fluctuations while maintaining local extrema and signal curvature. [43] This property is essential for the present study, as the time resolved comparison between RI and LC-PM-Sensor signals requires that peak amplitudes and short term concentration variations are not systematically attenuated by the filtering process. Figure 2.5 illustrates the characteristic effect of the applied filters on a representative RI time series, including the raw signal, the Savitzky Golay filtered signal, and a simple moving average (MA) with a window size of 10 data points for comparison. In linear representation of the particle number concentration, slight attenuation of local extrema introduced by the MA becomes apparent. Although both methods reduce high frequency measurement fluctuations, the MA leads to reduced peak amplitudes and slight temporal broadening of short term concentration events. The Savitzky Golay filter preserves the geometric characteristics of the signal more consistently and was therefore selected to minimize filter induced distortion while ensuring a reliable comparison between the RI and LC-PM-Sensor signals. The data (pre and postprocessed) were evaluated using OriginPro 2023 and Microsoft Excel.

2.3 Correction function measurements²

In order to evaluate and compare the measurement performance of the LC-PM-Sensors against that of the RI, both sensor types were installed in a measurement chamber (see Chapter 2.2.3). Two sets of measurements were conducted under varying relative humidity conditions in order to assess sensor performance un-

²Parts of this Chapter are published in Reinke et al. [32].

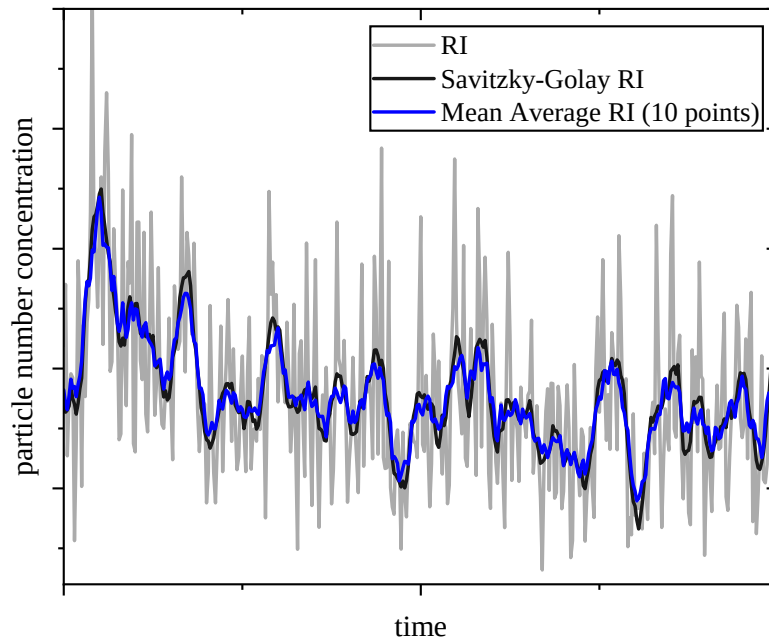


Figure 2.5: Exemplary RI particle number concentration time series comparing the raw signal (grey), the Savitzky–Golay filtered signal with a window size of 25 data points and a second order polynomial (black), and the 10-point moving average signal (blue).

der elevated relative humidity conditions comparable to those encountered in wet separator applications. As discussed previously (see Chapter 2.2.3), elevated relative humidity affects light scattering based sensor response and represents a relevant operating condition in industrial environments. The present measurements therefore assess sensor stability and robustness under humid conditions. These measurements form the basis for the correction of the total particle number concentration and particle size distribution of the LC-PM-Sensor. Figure 2.6 represents the results of the measurements performed. In the initial measurement condition (see Figure 2.6a)), the relative humidity was maintained at approximately 55 % at a temperature of 23 °C. The second measurement (see Figure 2.6b)) was conducted under conditions of high relative humidity (approximately 95 %) at a temperature of 23 °C. Figures 2.6a) and b) present the particle number concentration over time as recorded by one RI and five LC-PM-Sensors, respectively. Furthermore, the relative humidity is indicated. In both figures, a reference line is included to denote the maximum measurable particle num-

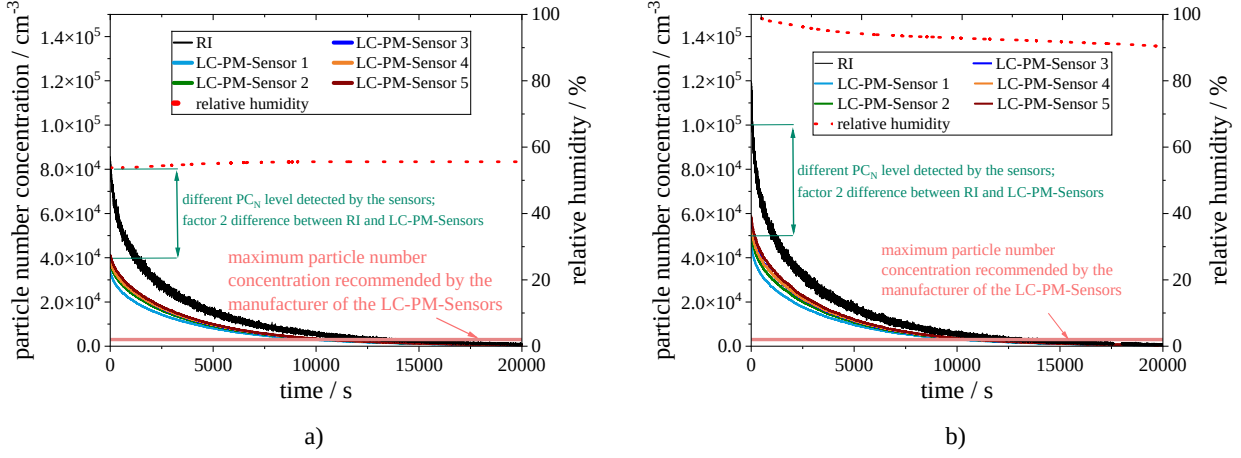


Figure 2.6: Particle number concentration measured by five LC-PM-Sensors and one RI over time in a measurement chamber (a): $rH \approx 55\%$, $T = 23^\circ\text{C}$; b): $rH \approx 95\%$, $T = 23^\circ\text{C}$). The relative humidity is given on a secondary coordinate axis. The maximum measurable particle number concentration of the LC-PM-Sensors is given as a red reference line. [32]

ber concentration of $3 \times 10^3 \text{ 1/cm}^3$ for the LC-PM-Sensors, as specified by the manufacturer [44]. The relative humidity, established within the chamber prior to the commencement of discontinuous particle dosing, remained consistent throughout the duration of the experiment. Over the course of 20000 s, the particle number concentration measured by both sensors decreased by three orders of magnitude. In conditions of ambient relative humidity, the RI recorded a maximum particle number concentration of approximately $8 \times 10^4 \text{ 1/cm}^3$, while the LC-PM-Sensors detected concentrations ranging from $3.3 \times 10^4 \text{ 1/cm}^3$ (LC-PM-Sensor 1) to $4.1 \times 10^4 \text{ 1/cm}^3$ (LC-PM-Sensor 5), with intermediate values of $3.7 \times 10^4 \text{ 1/cm}^3$ (LC-PM-Sensor 2), $3.9 \times 10^4 \text{ 1/cm}^3$ (LC-PM-Sensor 3), and $3.8 \times 10^4 \text{ 1/cm}^3$ (LC-PM-Sensor 4). To assess inter-sensor consistency, the simultaneously measured maximum concentrations of the LC-PM-Sensors were compared relative to their group mean under identical operating conditions. For dry conditions, the LC-PM-Sensor readings correspond to a maximum deviation of $\approx \pm 12\%$ from the group mean. In conditions of elevated relative humidity, the RI recorded a maximum particle number concentration of approximately $1 \times 10^5 \text{ 1/cm}^3$, while the LC-PM-Sensors registered concentrations between $4.5 \times 10^4 \text{ 1/cm}^3$ (LC-PM-Sensor 1) and $5.9 \times 10^4 \text{ 1/cm}^3$ (LC-PM-Sensor 5), with intermediate values of $4.9 \times 10^4 \text{ 1/cm}^3$ (LC-PM-Sensor 2), $5.2 \times 10^4 \text{ 1/cm}^3$

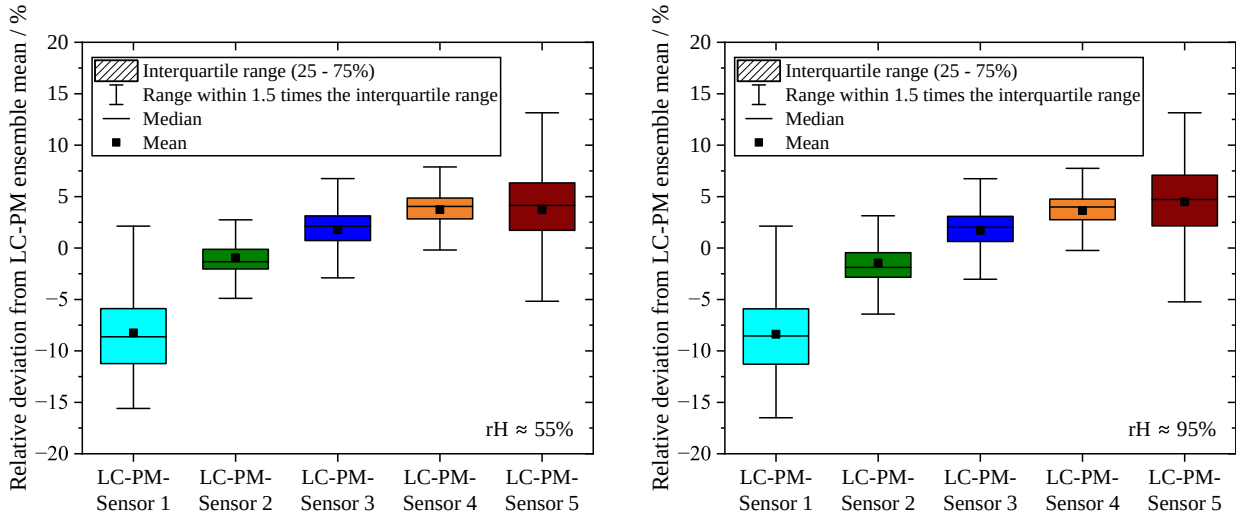


Figure 2.7: Relative deviation of the five LC-PM-Sensors from the LC-PM-Sensor ensemble mean concentration under dry and humid conditions.

(LC-PM-Sensor 3), and $5.5 \times 10^4 \text{ 1/cm}^3$ (LC-PM-Sensor 4). Under these conditions, the maximum deviation from the LC-PM-Sensor group mean increases to $\approx \pm 14 \%$. The results indicate a moderate increase in inter-sensor variability at elevated relative humidity, while inter-sensor variability remains on the same order of magnitude under both conditions. However, since the measurements were performed at particle number concentrations substantially exceeding the specified measurement range of the LC-PM-Sensor, the deviations cannot be directly evaluated against the precision limits stated in the datasheet. The results suggest the possibility of establishing correlations between the datasets, which could facilitate further investigation into the discrepancies in LC-PM-Sensor signals within the examined concentration range.

2.4 Inter-sensor variability of the LC-PM-Sensors

To quantify the inter-sensor variability of the five LC-PM-Sensors, the relative deviation of each sensor from the LC-PM-Sensor ensemble mean was evaluated for each time step. The resulting distributions of the relative deviation are shown in Fig. 2.7 for both investigated conditions ($rH \approx 55\%$ and $rH \approx 95\%$). The boxplots in Figure 2.7 illustrate the statistical distribution of the relative sensor deviations. Under dry conditions ($rH \approx 55\%$) LC-PM-Sensor 1 shows a negative bias

relative to the ensemble mean with a median deviation of approximately -9% . LC-PM-Sensor 2 exhibits only a small negative deviation of about -2% , while LC-PM-Sensors 3-5 show positive deviations. The median deviations of these sensors increased from approximately $+2\%$ for LC-PM-Sensor 3 to about $+5\%$ for LC-PM-Sensor 5. The interquartile ranges remain small for LC-PM-Sensors 2-4, indicating stable sensor behavior, whereas LC-PM-Sensors 1 and 5 show larger spreads. A similar pattern is observed under humid conditions ($rH \approx 95\%$). The relative ordering of the sensors remains largely unchanged, with LC-PM-Sensor 1 again exhibiting the largest negative deviation and LC-PM-Sensor 5 the largest positive deviation. This indicates that the observed differences between the sensors are primarily caused by systematic calibration offsets rather than humidity-dependent effects. To quantify the overall inter-sensor variability, statistical metrics of the relative standard deviation (RSD) and the mean absolute relative deviation (MARD) were calculated (Table 2.2). The mean RSD amounts to 5.75% under dry conditions and increased to 5.95% at high relative humidity. Similarly, the MARD rises from 4.25% to 4.46% . These values indicate a good agreement between the sensors, with deviations of individual sensors remaining below approximately 5% relative to the ensemble mean. The observed deviation in LC-PM-Sensor 1's response pattern compared to LC-PM-Sensors 2, 3, 4, and 5 may be attributed (but can't be verified) to its different production date, as it was manufactured in a different month than the other sensors. Overall, the results demonstrate a consistent sensor-to-sensor variability within the LC-PM-Sensor array. While small systematic biases between individual sensors are present, the overall spread of the measurements remains limited, confirming a stable and reproducible behavior of the LC-PM-Sensors under both dry and humid conditions.

Table 2.2: Statistical metrics of the inter-sensor deviation of the five LC-PM-Sensors.

Condition	Mean RSD / %	Median RSD / %	Max RSD / %	MARD / %
$rH \approx 55\%$	5.75	5.67	11.81	4.25
$rH \approx 95\%$	5.95	5.74	11.81	4.46

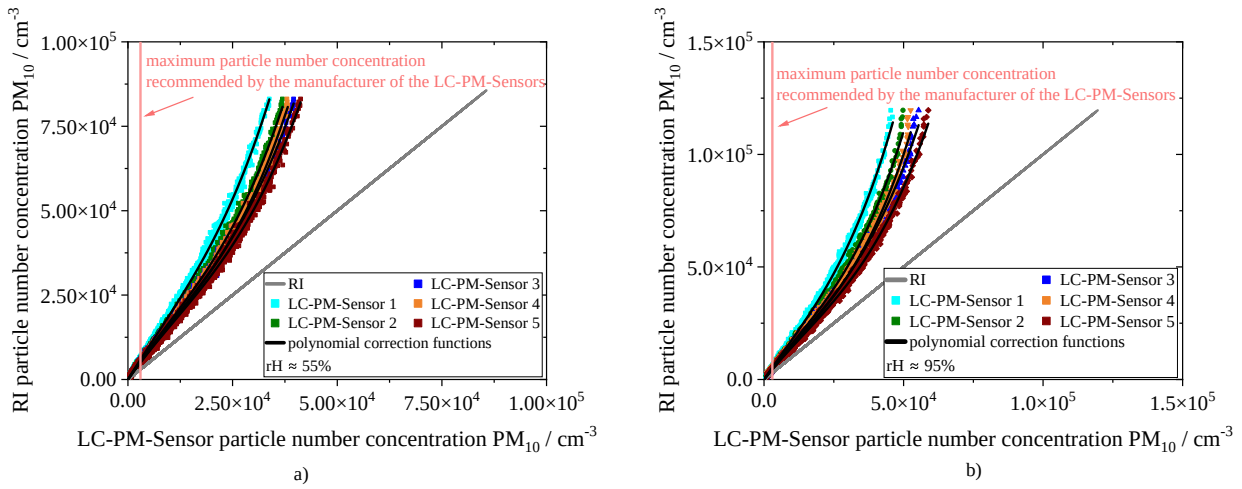


Figure 2.8: Scatter plot representation of the measurements performed in the measurement chamber at ambient (a): $rH \approx 55\%$ and humid (b): $rH \approx 95\%$ conditions. The maximum measurable particle number concentration of the LC-PM-Sensors is given as a red reference line. Third-order polynomial regression is shown in black. [32]

2.5 Data postprocessing to derive corrections functions for particle number concentrations measurements⁴

The total particle number concentration curves of the LC-PM Sensors and RIs displayed comparable qualitative trends. However, quantitative discrepancies were evident. Figure 2.8 illustrates the quantitative discrepancies by presenting the RI particle number concentration versus the LC-PM-Sensor particle number concentration in a scatter plot for each LC-PM-Sensor. A reference line has been included to indicate the maximum measurable particle number concentration of $3 \times 10^3 1/cm^3$ for the LC-PM-Sensors, as specified by the manufacturer [44]. The grey line represents the theoretical ideal agreement between the RI and LC-PM-Sensors. The correction function was determined through regression analysis, employing a third-degree polynomial fit to the scatter plot data points and is given in black. The selection of the third-degree polynomial order was based on the following criteria. Firstly, the coefficient of determination (R^2) was employed to guarantee an optimal fit between the corrected data and the reference measurements. Furthermore, the selected polynomial order was

⁴Parts of this Chapter are published in Reinke et al. [32].

Table 2.3: *Third-order polynomial correction functions and corresponding R^2 values for LC-PM-Sensors under ambient and humid conditions.*

LC-PM-Sensor	rH $\approx$ 55%	rH $\approx$ 95%
LC-PM-Sensor 1	$2.01366x - 1.83 \times 10^{-5}x^2 + 9.28 \times 10^{-10}x^3$ $R^2 = 0.99857$	$1.82125x - 1.12 \times 10^{-5}x^2 + 5.5 \times 10^{-10}x^3$ $R^2 = 0.99884$
LC-PM-Sensor 2	$1.8727x - 2.56 \times 10^{-5}x^2 + 9.24 \times 10^{-10}x^3$ $R^2 = 0.99855$	$1.69777x - 1.67 \times 10^{-5}x^2 + 5.36 \times 10^{-10}x^3$ $R^2 = 0.99873$
LC-PM-Sensor 3	$1.79601x - 2.35 \times 10^{-5}x^2 + 7.66 \times 10^{-10}x^3$ $R^2 = 0.99854$	$1.61744x - 1.51 \times 10^{-5}x^2 + 4.1 \times 10^{-10}x^3$ $R^2 = 0.99871$
LC-PM-Sensor 4	$1.78027x - 2.61 \times 10^{-5}x^2 + 9.12 \times 10^{-10}x^3$ $R^2 = 0.99856$	$1.61439x - 1.82 \times 10^{-5}x^2 + 5.17 \times 10^{-10}x^3$ $R^2 = 0.99866$
LC-PM-Sensor 5	$1.74706x - 2.46 \times 10^{-5}x^2 + 7.4 \times 10^{-10}x^3$ $R^2 = 0.99853$	$1.55832x - 1.6 \times 10^{-5}x^2 + 3.79 \times 10^{-10}x^3$ $R^2 = 0.99876$

required to maintain the accuracy of the correction across the entire concentration range, including the potential to correct for coincidence effects. Finally, the polynomial order was selected with the intention of achieving an accurate correction, while remaining as low as possible to avoid overfitting and maintain the simplicity of the model. The observed deviation in LC-PM-Sensor 1's response pattern compared to LC-PM-Sensors 2, 3, 4, and 5 may be attributed (but can't be verified) to its different production date, as it was manufactured in a different month than the other sensors. The coefficients of the third-order polynomial correction functions as well as the values of the corresponding coefficient of determination (R^2) for the regression analysis are presented in Table 2.3.

2.6 Data postprocessing to derive correction scales for particle size distribution measurements

In order to obtain and evaluate the dataset required for the derivation of the scaling functions for the particle size distribution, the following steps were taken. Following the pre-processing of the measurement data, post-processing

takes places. In the following section two scaling factors are introduced: one for scaling the total particle number concentration, α_1 (resulting in an uniform correction for all size classes), and one array of size class-specific factors $\alpha_{2,i}$ correcting for residual discrepancies in the counts of the individual size classes (originating e.g. from differences in the exact size classification between the LC-PM-Sensors and RIs). The first correction scale α_1 is defined as the ratio of the total particle number concentration of the RI and LC-PM-Sensor at each point of time (1 s interval):

$$\alpha_1 = \frac{PC_N^{RI}}{PC_N^{LC-PM-Sensor}}. \quad (2.4)$$

Figure 2.9 illustrates the scaling factor α_1 as a function of the total particle number concentration measured by each LC-PM-Sensor in the measurement chamber. Due to the frequent fluctuations in particle number concentration detected by the RI, particularly at low concentration levels, the set of calculated α_1 -values were approximated by a polynomial fit of 4th order. The frequent fluctuations of the α_1 -values is exemplary shown for LC-PM-Sensor 1, and were left out for LC-PM-Sensor 3, 4 and 5 for clarity. While LC-PM-Sensor 2 was deployed in later measurements, it was not considered in the particle size distribution analysis. The particle number concentration range below 1×10^3 1/cm³ was not considered in the determination of the polynomial. The selection of a polynomial fit for α_1 based on the same criteria as described above (see Chapter 2.2.4). The polynomial correction expressions for each individual sensor are presented in Table 2.4. The four LC-PM-Sensors showed similar behavior patterns across the particle number concentration range. At lower concentrations (below 1×10^4 1/cm³), LC-PM-Sensor 1 maintained a constant α_1 value, while sensors 3, 4, and 5 showed gradual changes and dropped to a minimum value at $\approx 1 \times 10^4$ 1/cm³. As particle number concentrations increased beyond 1×10^4 1/cm³, all sensors demonstrated a steep rise in α_1 values. Throughout the entire concentration range, sensors 3, 4, and 5 aligned closely with each other, whereas sensor 1 consistently displayed higher α_1 values, with all sensors showing α_1 values ranging from approximately 1.5 to 2.5. The observed deviation in LC-PM-Sensor 1's response pattern compared to LC-PM-Sensors 3, 4, and 5 may be attributed (but can't be verified) to its different production date, as it was manufactured in a different month than the other sensors. Variations between manufacturing batches may result in differences in internal calibration, which may affect the sensor output. Since the measurements were carried out at particle number concentrations above the specified measurement range

of the LC-PM-Sensors, the observed deviations cannot be directly compared with the precision limits given in the datasheet. The results therefore describe inter-sensor variability under these extended operating conditions. Consistent with previous findings [32], the LC-PM-Sensors tend to underestimate the total particle number concentration, necessitating an upward adjustment. This adjustment results in α_1 values exceeding 1 across the range of particle number concentrations considered.

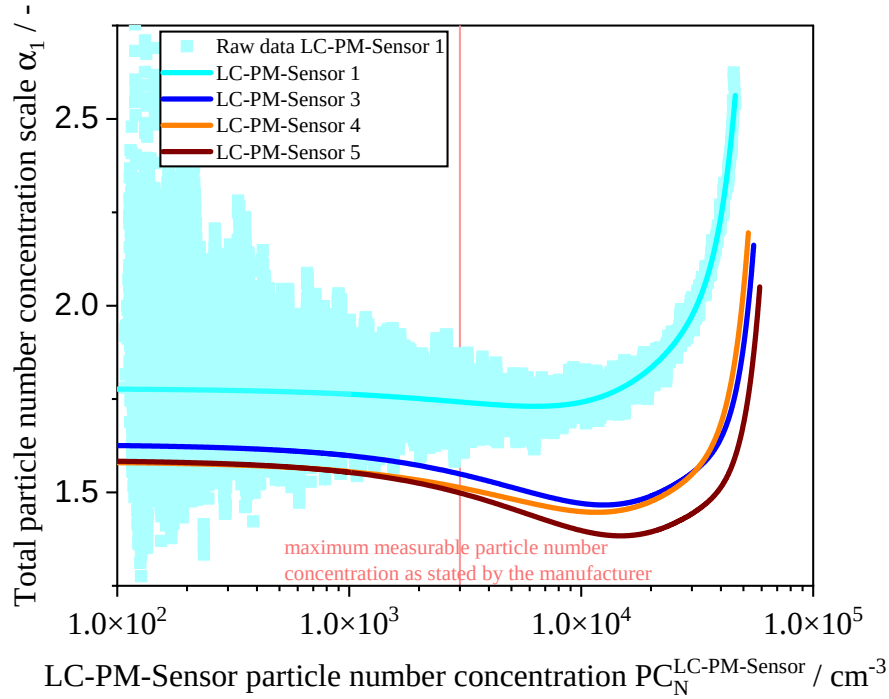


Figure 2.9: Total particle number concentration scale α_1 as a function of the total particle number concentration for the four LC-PM-Sensors.

Application of the correction factor α_1 to the LC-PM-Sensor dataset results in systematic bias across particle size classes, manifesting as overestimation in some size classes and underestimation in others due to coincidence effects. The bidirectional error pattern suggests that a single correction coefficient is insufficient to properly calibrate measurements across the entire particle size spectrum. This observation indicates that an additional scaling factor, $\alpha_{2,i}$, might be required to accurately adjust the particle size distribution of the sampled aerosol. The introduction of $\alpha_{2,i}$ accounts for variations in the measurement response that are not fully addressed by α_1 which corrects only for

Table 2.4: Polynomial functions 4th order of α_1 of the respective LC-PM-Sensor.

LC-PM-Sensor	rH $\approx$ 95%						R^2
$\alpha_1^{\text{LC-PM-Sensor 1}}$	1.77	—	1.69	$\times$	$10^{-5}(PC_N^{\text{LC-PM-Sensor}})$	+	0.81
	1.79	$\times$	$10^{-9}(PC_N^{\text{LC-PM-Sensor}})^2$	—	5.419	$\times$	
	$10^{-14}(PC_N^{\text{LC-PM-Sensor}})^3$			+	6.74	$\times$	
	$10^{-19}(PC_N^{\text{LC-PM-Sensor}})^4$						
$\alpha_1^{\text{LC-PM-Sensor 3}}$	1.62	—	3.24	$\times$	$10^{-5}(PC_N^{\text{LC-PM-Sensor}})$	+	0.77
	2.15	$\times$	$10^{-9}(PC_N^{\text{LC-PM-Sensor}})^2$	—	5.44	$\times$	
	$10^{-14}(PC_N^{\text{LC-PM-Sensor}})^3$			+	5.28	$\times$	
	$10^{-19}(PC_N^{\text{LC-PM-Sensor}})^4$						
$\alpha_1^{\text{LC-PM-Sensor 4}}$	1.58	—	2.87	$\times$	$10^{-5}(PC_N^{\text{LC-PM-Sensor}})$	+	0.76
	2.01	$\times$	$10^{-9}(PC_N^{\text{LC-PM-Sensor}})^2$	—	5.34	$\times$	
	$10^{-14}(PC_N^{\text{LC-PM-Sensor}})^3$			+	5.65	$\times$	
	$10^{-19}(PC_N^{\text{LC-PM-Sensor}})^4$						
$\alpha_1^{\text{LC-PM-Sensor 5}}$	1.58	—	3.51	$\times$	$10^{-5}(PC_N^{\text{LC-PM-Sensor}})$	+	0.74
	2.06	$\times$	$10^{-9}(PC_N^{\text{LC-PM-Sensor}})^2$	—	4.81	$\times$	
	$10^{-14}(PC_N^{\text{LC-PM-Sensor}})^3$			+	4.31	$\times$	
	$10^{-19}(PC_N^{\text{LC-PM-Sensor}})^4$						

the total particle number concentration. This provides a more comprehensive correction for the discrepancies between the LC-PM-Sensors and the RI in characterizing the particle size distribution. Due to the limited particle size classification of the LC-PM-Sensor, which comprises only five number-based bins and provides the corresponding particle number concentration as a cumulative value, the particle concentration $\Delta PC_{N,i}^{\text{LC}}$ within each individual size class i was calculated using the following expression:

$$\Delta PC_{N,i}^{\text{LC-PM-Sensor}} = PC_{N,i}^{\text{LC-PM-Sensor}} - PC_{N,i-1}^{\text{LC-PM-Sensor}} \quad (2.5)$$

Figure 2.10 schematically illustrates the particle size categorization, depicting the boundaries between $\Delta PC_{N,\text{PM}_{0.5}}$ (0.3-0.5 μm), $\Delta PC_{N,\text{PM}_{1.0}}$ (0.5-1.0 μm), and $\Delta PC_{N,\text{PM}_{2.5}}$ (1.0-2.5 μm) fractions. This approach employs distinct class boundaries that differ from the weighting functions used in $\text{PM}_{2.5}$ and PM_{10} immission measurements. The particle size classes $\Delta PC_{N,\text{PM}_4}$ and $\Delta PC_{N,\text{PM}_{10}}$ were excluded from the analysis due to the low particle counts within these size categories, which limits their statistical relevance. Also, the LC-PM-Sensors cannot measure these data directly and therefore extrapolate the $\Delta PC_{N,\text{PM}_4}$ and $\Delta PC_{N,\text{PM}_{10}}$ size

fractions (see Sec. 2.2.1). Corresponding particle size boundaries are applied to the RI data and can be directly selected within the PDAnalyze analysis software from the manufacturer. $\alpha_{2,i}$ is defined as the ratio of the particle number concentration of one particle size class of the RI to the particle number concentration of the same particle size class of the LC-PM-Sensor, after applying α_1 of the respective LC-PM-Sensor data at the given total number concentration at this point of time (1 s interval):

$$\alpha_{2,i} = \frac{\Delta PC_{N,i}^{RI}}{\alpha_1 \cdot \Delta PC_{N,i}^{LC-PM-Sensor}}. \quad (2.6)$$

Since α_1 is initially applied to the entire dataset, this factor must be subsequently accounted in the rescaling process for $\alpha_{2,i}$. For each value of $\Delta PC_{N,PM_i}$, a corresponding value for $\alpha_{2,i}$ is obtained, and this relationship can be described by an approximation function. The selection of the respective polynomial order for $\alpha_{2,i}$ was based on the following criteria. Firstly, the coefficient of determination (R^2) was employed to guarantee an optimal correlation between the α_1 -corrected LC-PM-Sensor data and the reference measurements. Furthermore, the selected polynomial order was required to maintain the accuracy of the correction across the entire concentration range, including the potential to correct for coincidence effects. Finally, the polynomial order was selected with the intention of achieving an accurate correction, while remaining as low as possible to avoid overfitting and maintain the simplicity of the model. Figure 2.11 presents the scaling factor $\alpha_{2,i}$ as a function of the particle number concentration of the respective sensor and particle size class i , measured in the measurement chamber. The particle size classes $\Delta PC_{N,PM4}$ and $\Delta PC_{N,PM10}$ were excluded from the analysis due to the low particle counts within these size categories, which limits their statistical relevance. In contrast to the findings shown in Figure 2.9, all sensors exhibit similar behavior across the investigated particle size classes. Deviations between the LC-PM-Sensors and the reference are represented by the correction factor $\alpha_{2,i}$, where $\alpha_{2,i} > 1$ indicates underestimation and $\alpha_{2,i} < 1$ indicates overestimation of the particle number concentration within the respective LC-PM-Sensor size class. The smallest particle size class, $\Delta PC_{N,PM0.5}$, is consistently underestimated over the entire investigated particle number concentration range within this class (1×10^2 1/cm³ to $\approx 3 \times 10^4$ 1/cm³). The corresponding correction factors remain between approximately 1.1 to 1.5. For $\Delta PM_{1.0}$, underestimation of the particle number concentration within this size class occurs up to approximately 1×10^4 1/cm³. In this range, $\alpha_{2,i}$ varies between 1.0 to 1.2. At elevated particle number concentrations within the same

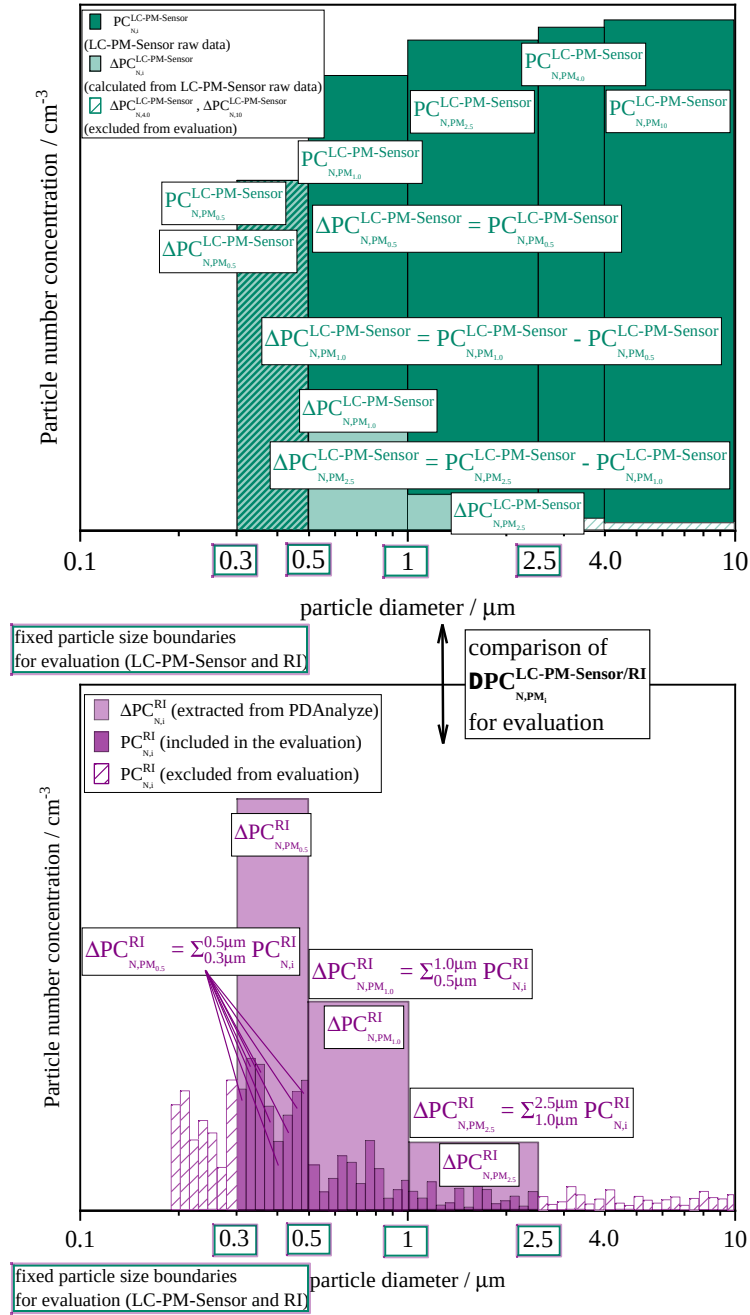


Figure 2.10: Schematic representation of particle size categorization showing the boundaries between particle number concentration fractions $\Delta PC_{N,PM_{0.5}}$ (0.3-0.5 μm), $\Delta PC_{N,PM_{1.0}}$ (0.5-1.0 μm), and $\Delta PC_{N,PM_{2.5}}$ (1.0-2.5 μm).

size class, this fraction is overestimated, and the correction factor decreases to approximately 0.7 to 1.0. The $\Delta PM_{2.5}$ size class is overestimated across the entire investigated concentration range within this class, with $\alpha_{2,i}$ decreasing from approximately 0.58 to 0.25 as the particle number concentration in this size class increases. For low particle concentrations, the values of $\alpha_{2,i}$ appear to converge toward a constant value, suggesting stabilization in the correction factor across the smaller range of particle number concentrations, followed by a sharp decrease or increase at elevated particle number concentrations, similar to the trends observed in Figure 2.9. The deviations in measurement accuracy observed in the LC-PM-Sensors can be largely explained by coincidence effects, particularly at elevated particle number concentrations. These effects lead to an undercounting of small particles and an overcounting of larger particles. The introduction of the scaling factor $\alpha_{2,i}$ helps correct these errors by adjusting the measured particle size distributions to better align with the true particle concentrations, as verified by the RI. The stabilization of $\alpha_{2,i}$ at lower concentrations reflects the reduced impact of coincidence effects at these conditions, leading to a more accurate assessment of the particle size distribution. Coincidence effects in sizing occurring in the measurement are not affected by α_1 and should be corrected by $\alpha_{2,i}$. The deviation from linear behavior at elevated particle concentrations can be attributed to coincidence effects. Consistent with this explanation, the deviation from linearity begins at lower particle concentrations for larger particle size classes. Although $\alpha_{2,i}$ remains nearly constant at very low concentrations, the values still deviate from 1. This suggests that the discrepancy in particle size distribution measurements between the RI and LC-PM-Sensors may also be caused by factors such as differences in class assignment methodologies. Table 2.5 presents the exact formulas of the polynomial correction functions for $\alpha_{2,i}$.

The corrected total particle number concentration of the LC-PM-Sensors is calculated as follows:

$$P_{N,\text{corrected}}^{\text{LC-PM-Sensor}} = P_N^{\text{RI}} = \alpha_1 \cdot P_N^{\text{LC-PM-Sensor}} = \sum_i \alpha_1 \cdot \Delta P_{N,i}^{\text{LC-PM-Sensor}}. \quad (2.7)$$

The corrected size resolved particle number concentration is calculated as follows:

$$\Delta P_{N,i,\text{corrected}}^{\text{LC-PM-Sensor}} = \Delta P_{N,i}^{\text{RI}} = \alpha_{2,i} \cdot \alpha_1 \cdot \Delta P_{N,i}^{\text{LC-PM-Sensor}}. \quad (2.8)$$

After installation of the sensors in the wet separation test facility (see Chapter

Table 2.5: Polynomial functions of $\alpha_{2,i}$ of the respective LC-PM-Sensor, subdivided into $\Delta PC_{N,PM_{0.5}}$, $\Delta PC_{N,PM_{1.0}}$, and $\Delta PC_{N,PM_{2.5}}$.

LC-PM-Sensor	rH $\approx$ 95%	R^2
$\alpha_2^{\text{LC-PM-Sensor 1}}$	$\Delta PC_{N,PM_{0.5}}: 1.02 + 1.37 \times 10^{-5}(PC_{N,\Delta PM_{0.5}}^{\text{LC-PM-Sensor 1}}) -$	0.87
	$5.78 \times 10^{-11}(PC_{N,\Delta PM_{0.5}}^{\text{LC-PM-Sensor 1}})^2 + 3.65 \times$	
	$10^{-14}(PC_{N,\Delta PM_{0.5}}^{\text{LC-PM-Sensor 1}})^3 - 1.34 \times$	
	$10^{-18}(PC_{N,\Delta PM_{0.5}}^{\text{LC-PM-Sensor 1}})^4$	
	$\Delta PC_{N,PM_{1.0}}: 1.20 - 5.26 \times 10^{-5}(PC_{N,\Delta PM_{1.0}}^{\text{LC-PM-Sensor 1}}) +$	0.89
	$4.33 \times 10^{-9}(PC_{N,\Delta PM_{1.0}}^{\text{LC-PM-Sensor 1}})^2 - 2.74 \times$	
	$10^{-13}(PC_{N,\Delta PM_{1.0}}^{\text{LC-PM-Sensor 1}})^3$	
	$\Delta PC_{N,PM_{2.5}}: 0.57 + 9.34 \times 10^{-6}(PC_{N,\Delta PM_{2.5}}^{\text{LC-PM-Sensor 1}}) -$	0.87
	$8.84 \times 10^{-9}(PC_{N,\Delta PM_{2.5}}^{\text{LC-PM-Sensor 1}})^2$	
$\alpha_2^{\text{LC-PM-Sensor 3}}$	$\Delta PC_{N,PM_{0.5}}: 1.03 + 1.42 \times 10^{-5}(PC_{N,\Delta PM_{0.5}}^{\text{LC-PM-Sensor 3}}) -$	0.83
	$1.03 \times 10^{-9}(PC_{N,\Delta PM_{0.5}}^{\text{LC-PM-Sensor 3}})^2 + 6.91 \times$	
	$10^{-14}(PC_{N,\Delta PM_{0.5}}^{\text{LC-PM-Sensor 3}})^3 - 1.22 \times$	
	$10^{-18}(PC_{N,\Delta PM_{0.5}}^{\text{LC-PM-Sensor 3}})^4$	
	$\Delta PC_{N,PM_{1.0}}: 1.15 - 1.94 \times 10^{-5}(PC_{N,\Delta PM_{1.0}}^{\text{LC-PM-Sensor 3}}) +$	0.86
	$3.97 \times 10^{-10}(PC_{N,\Delta PM_{1.0}}^{\text{LC-PM-Sensor 3}})^2 - 7.66 \times$	
	$10^{-14}(PC_{N,\Delta PM_{1.0}}^{\text{LC-PM-Sensor 3}})^3$	
	$\Delta PC_{N,PM_{2.5}}: 0.54 + 2.23 \times 10^{-5}(PC_{N,\Delta PM_{2.5}}^{\text{LC-PM-Sensor 3}}) -$	0.82
	$7.51 \times 10^{-9}(PC_{N,\Delta PM_{2.5}}^{\text{LC-PM-Sensor 3}})^2$	
$\alpha_2^{\text{LC-PM-Sensor 4}}$	$\Delta PC_{N,PM_{0.5}}: 1.02 + 1.54 \times 10^{-5}(PC_{N,\Delta PM_{0.5}}^{\text{LC-PM-Sensor 4}}) -$	0.85
	$1.44 \times 10^{-9}(PC_{N,\Delta PM_{0.5}}^{\text{LC-PM-Sensor 4}})^2 + 1.04 \times$	
	$10^{-13}(PC_{N,\Delta PM_{0.5}}^{\text{LC-PM-Sensor 4}})^3 - 1.96 \times$	
	$10^{-18}(PC_{N,\Delta PM_{0.5}}^{\text{LC-PM-Sensor 4}})^4$	
	$\Delta PC_{N,PM_{1.0}}: 1.19 - 3.17 \times 10^{-5}(PC_{N,\Delta PM_{1.0}}^{\text{LC-PM-Sensor 4}}) +$	0.88
	$1.73 \times 10^{-9}(PC_{N,\Delta PM_{1.0}}^{\text{LC-PM-Sensor 4}})^2 - 1.34 \times$	
	$10^{-13}(PC_{N,\Delta PM_{1.0}}^{\text{LC-PM-Sensor 4}})^3$	
	$\Delta PC_{N,PM_{2.5}}: 0.55 + 2.45 \times 10^{-5}(PC_{N,\Delta PM_{2.5}}^{\text{LC-PM-Sensor 4}}) -$	0.83
	$8.52 \times 10^{-9}(PC_{N,\Delta PM_{2.5}}^{\text{LC-PM-Sensor 4}})^2$	
$\alpha_2^{\text{LC-PM-Sensor 5}}$	$\Delta PC_{N,PM_{0.5}}: 1.05 + 1.80 \times 10^{-5}(PC_{N,\Delta PM_{0.5}}^{\text{LC-PM-Sensor 5}}) -$	0.86
	$1.19 \times 10^{-9}(PC_{N,\Delta PM_{0.5}}^{\text{LC-PM-Sensor 5}})^2 + 7.25 \times$	
	$10^{-14}(PC_{N,\Delta PM_{0.5}}^{\text{LC-PM-Sensor 5}})^3 - 1.29 \times$	
	$10^{-18}(PC_{N,\Delta PM_{0.5}}^{\text{LC-PM-Sensor 5}})^4$	
	$\Delta PC_{N,PM_{1.0}}: 1.13 - 2.07 \times 10^{-5}(PC_{N,\Delta PM_{1.0}}^{\text{LC-PM-Sensor 5}}) +$	0.85
	$5.86 \times 10^{-10}(PC_{N,\Delta PM_{1.0}}^{\text{LC-PM-Sensor 5}})^2 - 6.16 \times$	
	$10^{-14}(PC_{N,\Delta PM_{1.0}}^{\text{LC-PM-Sensor 5}})^3$	
	$\Delta PC_{N,PM_{2.5}}: 0.51 + 2.23 \times 10^{-5}(PC_{N,\Delta PM_{2.5}}^{\text{LC-PM-Sensor 5}}) -$	0.80
	$6.10 \times 10^{-9}(PC_{N,\Delta PM_{2.5}}^{\text{LC-PM-Sensor 5}})^2$	

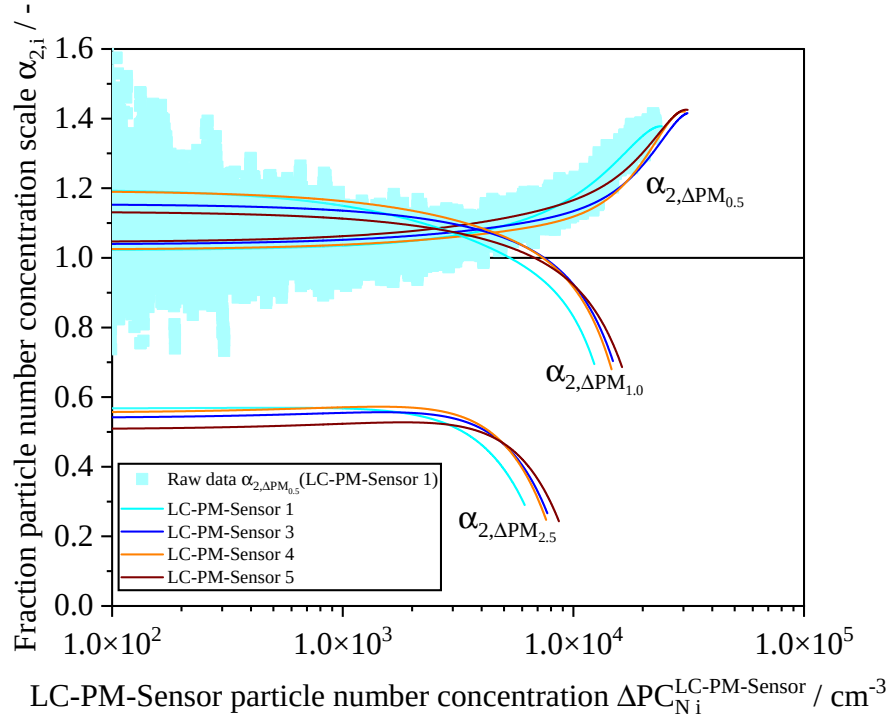


Figure 2.11: Fraction particle number concentration scale as a function of the fraction particle number concentration for the four LC-PM-Sensors. The polynomial correction functions for the corresponding LC-PM-Sensors and their validity are given in Table 2.53.

3.2), the same data pre-processing method as described above was applied. Subsequently, the correction function was implemented (based on the α_1 and $\alpha_{2,i}$ values derived from the measurement chamber), and the suitability of the correction was also evaluated by calculating the relative error as follows:

$$\text{relative error}_i = \frac{\Delta PC_{N,i}^{\text{LC-PM-Sensor}} - \Delta PC_{N,i}^{\text{RI}}}{\Delta PC_{N,i}^{\text{RI}}}. \quad (2.9)$$

The application of the scaling factors α_1 and $\alpha_{2,i}$ to the measured particle number concentrations of the LC-PM-Sensors allows for the adjustment of both the total particle number concentration and the particle size distribution, ensuring accurate representation across varying particle concentration levels within the aerosol.

Table 2.6: Generalized polynomial functions of $\alpha_{2,i}$, subdivided into $\Delta PC_{N,PM_{0.5}}$, $\Delta PC_{N,PM_{1.0}}$, and $\Delta PC_{N,PM_{2.5}}$.

	rH $\approx$ 95%	R^2
$\alpha_{2,\Delta PC_{N,PM_{0.5}}}$	$1.03 + 1.53 \times 10^{-5}(PC_{N,\Delta PM_{0.5}}^{LC-PM-Sensor}) - 9.30 \times 10^{-10}(PC_{N,\Delta PM_{0.5}}^{LC-PM-Sensor})^2 + 7.06 \times 10^{-14}(PC_{N,\Delta PM_{0.5}}^{LC-PM-Sensor})^3 - 1.45 \times 10^{-18}(PC_{N,\Delta PM_{0.5}}^{LC-PM-Sensor})^4$	1
$\alpha_{2,\Delta PC_{N,PM_{1.0}}}$	$1.17 - 3.11 \times 10^{-5}(PC_{N,\Delta PM_{1.0}}^{LC-PM-Sensor}) + 1.76 \times 10^{-9}(PC_{N,\Delta PM_{1.0}}^{LC-PM-Sensor})^2 - 1.37 \times 10^{-13}(PC_{N,\Delta PM_{1.0}}^{LC-PM-Sensor})^3$	1
$\alpha_{2,\Delta PC_{N,PM_{2.5}}}$	$0.54 + 1.96 \times 10^{-5}(PC_{N,\Delta PM_{2.5}}^{LC-PM-Sensor}) - 7.74 \times 10^{-9}(PC_{N,\Delta PM_{2.5}}^{LC-PM-Sensor})^2$	1

2.6.1 Generalized polynomial correction approach

The polynomial representations of $\alpha_{2,i}$ exhibited consistent behavioral characteristics across multiple sensors (Figure 2.11). Consequently, this study investigated the feasibility of implementing a generalized polynomial correction approach for particle number concentrations across the investigated three distinct size classes: $\Delta PC_{N,PM_{0.5}}$, $\Delta PC_{N,PM_{1.0}}$, and $\Delta PC_{N,PM_{2.5}}$. The primary objective was to determine whether a standardized correction methodology could eliminate the requirement for sensor-specific $\alpha_{2,i}$ correction. The polynomial correction factors for each particle size fraction were derived through averaging of the polynomials of all LC-PM-Sensors for the respective particle size class. The resultant averaged polynomials for each size class are comprehensively documented in Table 2.6.

2.7 Analysis of Particle Size Distribution Behavior in the Measurement Chamber

To assess and compare the particle size distribution measurement performance of the LC-PM-Sensors relative to the RI, both sensor types were installed within the controlled measurement chamber (see Section 2.2.3). Figure 2.12 shows the cumulative number-based particle size distribution Q_0 as a function of particle diameter for dry conditions (55 % rH) and humid conditions (95 % rH). For each humidity condition, the distributions were evaluated at three representative stages of the measurement, corresponding to high, intermediate,

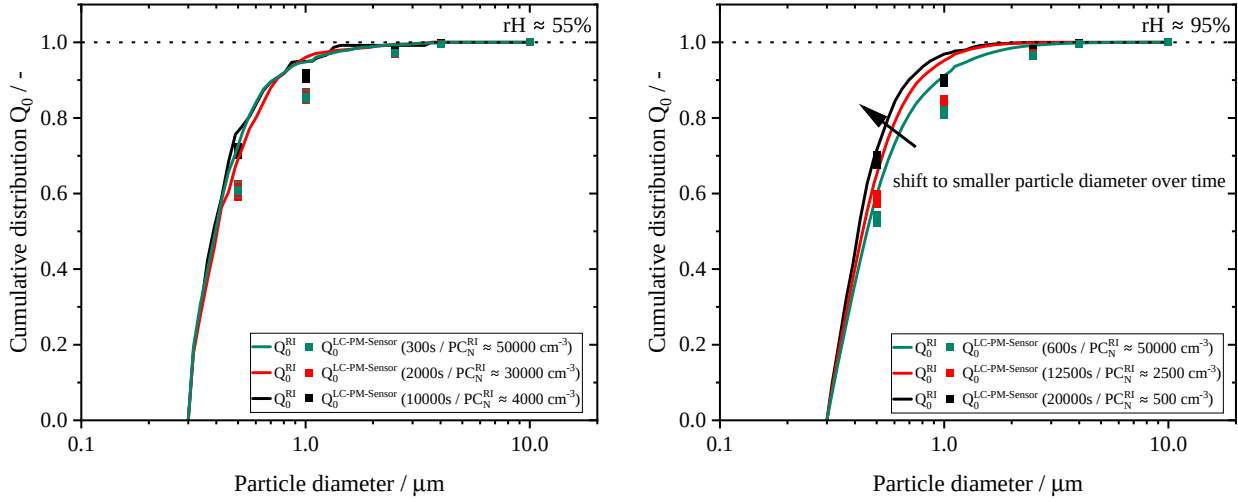


Figure 2.12: Number based particle size distribution Q_0 of four LC-PM-Sensors (squares) and of the RI (lines) at three different time stamps and different humidity conditions (left: 55% rH, right: 95% rH) in the measurement chamber.

and low particle number concentrations. Under dry conditions, these stages are represented by approximately 300 s, 2000 s, and 10 000 s, while under humid conditions they are represented by approximately 600 s, 12 500 s, and 20 000 s. The corresponding RI particle number concentrations are approximately 5×10^4 $1/\text{cm}^3$, 3×10^4 $1/\text{cm}^3$, and 4×10^3 $1/\text{cm}^3$ for the dry case, and approximately 5×10^4 $1/\text{cm}^3$, 2.5×10^3 $1/\text{cm}^3$, and 5×10^2 $1/\text{cm}^3$ for the humid case. As in the previous evaluation, one RI and four LC-PM-Sensors were considered. The individual LC-PM-Sensors are not shown separately in this figure, since the present discussion focuses on the qualitative PSD behavior rather than on sensor-to-sensor variability. For both humidity conditions, the RI data shows a gradual shift of the cumulative distribution towards smaller particle diameters as the measurement proceeds and the particle number concentration decreases. The LC-PM-Sensor data follow the same qualitative trend. Under dry conditions, however, this temporal shift remains small. In contrast, under humid conditions the shift is more pronounced. This indicates that the particle population changes more strongly over time at elevated relative humidity. At the same time, the overall shape of the distributions remains comparable, suggesting that the observed effect is not caused by a completely different aerosol regime but by a modification of the relative weighting of specific size ranges. This interpretation is supported by the corresponding differential number-based distributions q_0

shown in Appendix in Figure C.1. The q_0 data do not indicate a shift of the entire distribution towards larger or smaller diameters. Instead, the main differences between dry and humid conditions occur in the approximate size range from $0.3\ \mu\text{m}$ to $0.7\ \mu\text{m}$. At early measurement stages, the dry distributions exhibit comparatively higher contributions at smaller particle diameters, whereas the humid distributions show relatively higher contributions in the intermediate diameter range. With increasing measurement time, these differences become smaller. A pronounced intrinsic hygroscopic growth of the limestone particles is unlikely to be the dominant explanation for this behavior. First, the dispersed powder consisted of pure limestone and was introduced into the chamber using dry compressed air, so that the particles were not exposed to elevated humidity during the dispersion step itself. Second, the measured q_0 distributions do not show a uniform shift that would be expected if all particles increased in size in a similar manner. Instead, the results point to a humidity-dependent modification of the particle population after entry into the chamber. A plausible explanation could therefore be a change in the agglomeration state, which would mainly affect the relative contribution of intermediate and larger particle sizes. In this context, the stronger temporal shift observed for 95 % rH suggests that elevated humidity modifies the PSD evolution in the chamber more strongly than under dry conditions. It should also be noted that the decrease in particle number concentration is primarily driven by the constant sampling flow of the RI. Therefore, the differences observed in Q_0 cannot be explained solely by a faster overall decay of particle number concentration under humid conditions. With regard to the measurement behavior of the LC-PM-Sensors, it is noteworthy that the LC-PM-Sensor-based distributions reproduce not only the shape of the RI-based Q_0 curves but also the minimal temporal changes of the particle size distribution. Even under dry conditions, where the temporal shift of the RI distribution is comparatively small, the LC-PM-Sensors still indicate the same qualitative direction of change. Under humid conditions, where the shift is more pronounced, the agreement between LC-PM-Sensor and RI is even more apparent. This demonstrates that the LC-PM-Sensors are capable of detecting not only major differences in particle size distribution, but also comparatively small changes in the PSD over time. In this respect, the LC-PM-Sensors do not reflect random fluctuations, but show a measurement response that is consistent with the RI. To further quantify the measurement behavior of the LC-PM-Sensors and their deviation from the RI under controlled conditions, two scaling factors (α_1 , $\alpha_{2,i}$, see Section 2.6) were introduced.

2.8 Conclusion

The objective of this study was to evaluate the feasibility of in-line particle number concentration and particle size distribution measurements in gas-particle separation processes using LC-PM-Sensors. For this purpose, five LC-PM-Sensors were operated in parallel with a RI under controlled laboratory conditions at 55 % and 95 % relative humidity, representing conditions relevant for wet separation systems.

The deviation between the LC-PM-Sensors and the RI reference showed no relevant dependence on relative humidity. For both 55 % and 95 % relative humidity, the LC-PM-Sensors exhibited a comparable concentration dependent response. For concentrations up to approximately $6 \times 10^4 \text{ 1/cm}^3$, the deviations between LC-PM-Sensors and RI measurements could be described by a third-order polynomial correction function, with sensor-specific coefficients.

The inter-sensor comparison showed a consistent sensor-to-sensor response with only limited variability within the LC-PM-Sensor array. Although small systematic offsets between individual sensors were observed, the overall variability remained low. The mean relative standard deviation increased only slightly from 5.75 % at 55 % relative humidity to 5.95 % at 95 %, while the mean absolute relative deviation changed from 4.25 % to 4.46 %. This indicates that the differences between sensors were mainly caused by systematic calibration offsets rather than by humidity dependent effects. LC-PM-Sensor 1 showed a consistently different response, which may be related to its different production date.

The LC-PM-Sensors also reproduced the general shape and temporal evolution of the RI based particle size distributions under both dry and humid conditions. PSD shifts were more pronounced at high relative humidity, especially in the size range from approximately $0.3 \mu\text{m}$ to $0.7 \mu\text{m}$, indicating a change in distribution shape rather than uniform particle growth. A change in particle agglomeration state is therefore a plausible explanation. The LC-PM-Sensors captured these variations consistently and also resolved the trends in the $\Delta\text{PC}_{\text{N,PM}_{0.5}}$, $\Delta\text{PC}_{\text{N,PM}_{1.0}}$, and $\Delta\text{PC}_{\text{N,PM}_{2.5}}$ fractions in agreement with the RI reference.

Based on these results, a correction factor α_1 was introduced for total particle number concentration and a set of correction factors $\alpha_{2,i}$ for the individual PSD size classes. Both showed slight sensor-specific variation and can therefore be determined individually. Their combined application enabled correction of both total particle number concentration and PSD.

Overall, the results demonstrate that the investigated LC-PM-Sensors are suit-

able for monitoring particle number concentration and particle size distribution above their specified particle concentration under controlled conditions.

3

Application of Low-Cost PM-Sensors for Emission Characterization of a Wet Separator

In this chapter, the LC-PM-Sensors characterized in the previous section are implemented in a wet separator to evaluate their measurement performance. While the laboratory experiments provided controlled boundary conditions for assessing sensor behavior at defined particle concentrations and size distributions, the wet separator environment introduces additional influencing factors such as fluctuating dust concentrations and varying local gas velocities. These conditions represent typical industrial operating parameters and therefore serve as a basis for examining the practical applicability of LC-PM-Sensors in process-integrated particle monitoring. The objective of this investigation is to determine whether the LC-PM-Sensors are capable of detecting the local particle number concentration, particle size distribution, and spatial or temporal concentration fluctuations within the wet separator. The ability to resolve such local variations is essential for generating process-relevant information. The LC-PM-Sensor measurements are compared with data obtained from the established particle reference instrumentation used previously. This comparison enables an evaluation of the extent to which the correction scaling factors derived under laboratory conditions remains valid in a wet separation process, and whether LC-PM-Sensors can serve as suitable tools for in-line monitoring of particle related process parameters.

3.1 Wet Separators

All separators operate according to the same principle: the trajectory of a particle in the fluid must intersect a region or surface from which it can no longer be removed by the continuous phase. These regions or surfaces vary with the separation mechanism and are referred to as collectors. For filters, the collector is the filter surface; for wet separators, it is the droplet surface [4]. The primary types of separators are inertial separators, filtration separators, electrostatic precipitators and wet separators. The following discussion is limited to wet separators, as they are the subject of this chapter.

3.1.1 Principle of operation

In wet separators, particles interact with scrubbing liquid introduced as droplets and adhere to their surfaces [45]. The resulting particle-droplet agglomerates are removed from the gas stream by conventional separation mechanisms [4]. The fundamental processes in wet separators can be divided into four steps:

- i Dispersion of washing liquid into droplets in the aerosol stream
- ii Collision of the particles with droplets
- iii Adhesion of particles to droplet surfaces
- iv Separation of particle-laden droplets downstream

3.1.2 Deposition of particles onto individual droplets

The deposition process is analogous to particle deposition on single fibers [46]. It consists of two stages: particle transport to the droplet surface and particle adhesion. The separation efficiency $\varphi(d_p)$ is therefore expressed as the product of the collision efficiency $\eta(d_p)$ and the adhesion probability $h(d_p)$ as a function of particle diameter d_p [46].

$$\varphi(d_p) = \eta(d_p) \cdot h(d_p) \quad (3.1)$$

Figure 3.1 shows a schematic representation of a spherical droplet in an aerosol flow. Particles in the flow may reach the droplet surface through the transport mechanisms diffusion (a), inertia (b) and electrostatic forces (c) [47]. Diffusion is caused by the stochastic motion of particles. Electrostatic effects occur if a potential difference exists between droplet and particle. Inertial effects occur

when particles, depending on size or mass and the flow velocity, cannot follow streamline deflection and impact the droplet. According to Barth [48], inertial effects dominate particle transport to the droplet surface. Experimental results by Schuch [49] confirm this assumption.

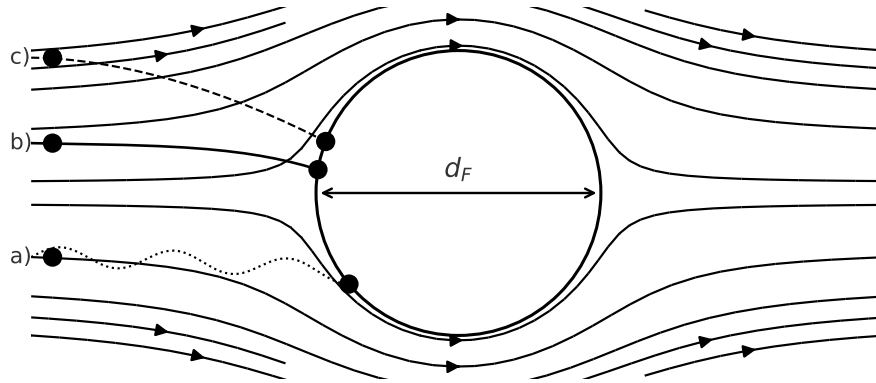


Figure 3.1: Schematic representation of transport mechanisms acting on a spherical surface. a) Diffusion, b) Inertia, c) Electrostatic forces, D_F droplet diameter.

3.1.3 State of the Art in Wet Separation

Wet separators can be classified according to their design and the method of liquid introduction. The seven types defined in [50] are spray scrubbers, packed- or tray columns, jet scrubbers, vortex scrubbers, rotary scrubbers and disintegrators, venturi scrubbers, bubble columns. Table 3.1 summarizes characteristic values for the relative velocity v between the aerosol and the scrubbing liquid in the contact zone of the scrubber, the overall pressure drop Δp , the energy demand E per 1000 m³, the liquid-to-gas ratio μ_W , and the cut-off diameter d_s , for selected scrubber types. The selection is limited to scrubbers whose droplet formation and liquid introduction mechanisms are most similar to the scrubber investigated in this work. The wet separator investigated in this study can be considered an intermediate design between venturi, jet and vortex separators, as it combines both droplet generation mechanisms. In the washer unit of the investigated wet separator, the aerosol first passes through a novel nozzle. Within this nozzle, a reduction in cross-sectional area causes the washing liquid to be drawn in through tubes immersed in the liquid reservoir. Upon entering the flow channel, the washing liquid is dispersed by the gas stream, and the resulting

three-phase mixture enters the vortex chamber. In the vortex chamber, the swirling washing liquid generates a highly turbulent flow, which promotes further droplet formation through continuous coalescence and breakup processes. Particle separation occurs when particles collide with and are captured by these droplets. After contact, particle adhesion to the droplets can be assumed. The droplet-laden gas stream then passes through a downstream droplet separator, where larger droplets are removed by inertial deflection and smaller droplets by a wire-mesh coalescence stage.

In principle, scrubbers differ in the method of droplet generation and in the

Table 3.1: *Characteristic values of typical wet scrubbers. v = relative velocity between the aerosol and the scrubbing liquid in the contact zone of the scrubber, Δp = total pressure drop, E = energy demand per 1000 cm³, μ_w = liquid-to-gas ratio, d_s = cut-off diameter in μm determined for test dust with a particle density of 2.42 gcm⁻³. From [50]*

Designation	Jet scrubber	Venturi scrubber	Bubble column	Vortex scrubber
v in m/s	5 – 15	30 – 150	5 – 15	8 – 40
Δp in hPa	0 – 10	20 – 200	15 – 25	2 – 10
E in kWh	1.2 – 3	0.7 – 7	1 – 4	4 – 15
μ_w in L/m ³	2 – 10	1 – 5	–	1 – 3
d_s in μm	0.8 – 0.9	<0.1 – 5	0.8 – 0.9	0.3 – 0.6

type of mixing between aerosol and scrubbing liquid. The following discussion of droplet formation is restricted to jet, venturi, and vortex scrubbers, as these concepts are most similar to the scrubber under investigation. In venturi scrubbers, droplet formation occurs in the throat of the constricted section. The scrubbing liquid is introduced at low pressure. Due to the locally high gas velocities, the liquid is dispersed under significant energy input. The droplets formed capture dust particles along the flow. Jet scrubbers operate similarly to water jet pumps. The scrubbing liquid is injected at several bar overpressure together with the aerosol in co-current flow, resulting in droplet formation and gas induction. As in venturi scrubbers, the gas stream is faster than the droplets travel, causing inertial deposition of particles onto the droplets. Although the basic design of jet and venturi scrubbers is similar, their operating parameters differ significantly (see Table 3.1). Vortex scrubbers direct the particle-laden

gas onto or over the liquid surface, inducing turbulence. At tear-off edges, the liquid is dispersed into droplets, leading to droplet formation and intensive mixing with the aerosol [50]. The removal of particle laden droplets from the gas stream requires downstream droplet separators. In principle, any other type of separator, such as electrostatic precipitators or cyclones, can be employed. The choice depends on the application.

3.2 Experimental Setup¹

To investigate the potential of in-line particle concentration measurements in gas-particle separation processes, the LC-PM-Sensors were installed downstream of the droplet separator in a wet separation test facility. A schematic representation of the wet separation test facility is provided in Figure 3.2.

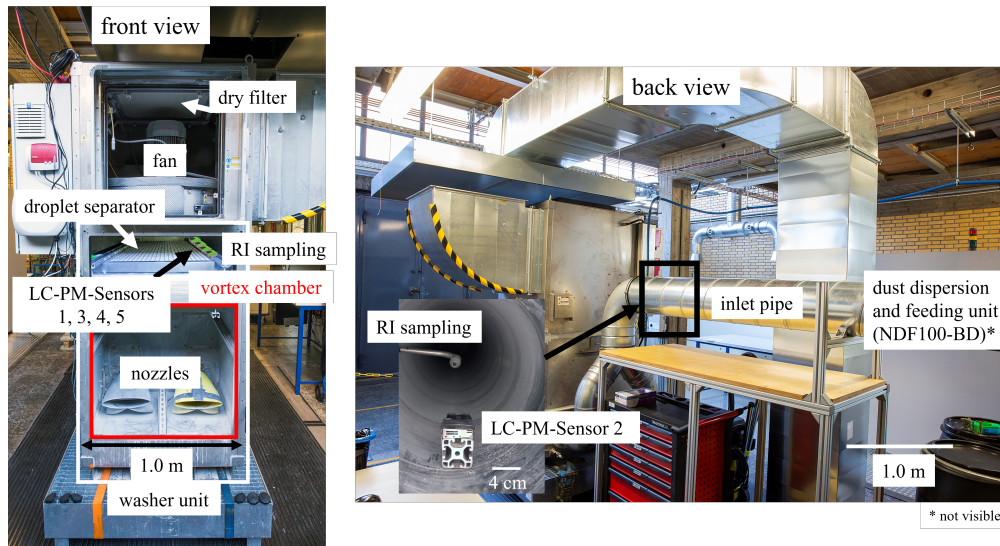


Figure 3.2: *Fotographic representation of the wet separator test facility.*

The test facility comprises two distinct units. The first stage of the process is the generation and characterization of the aerosol. This unit comprises a brush disperser (NDF100-BD, see Chapter 2.2.2) for the generation of the aerosol, followed by an inlet pipe. The particles were introduced at the centre line into the inlet pipe, which is 3 m in length and has a diameter of 0.25 m. At the end of the inlet pipe, the aerosol was analysed by a RI (Palas Promo 2000H with

¹Parts of this Chapter are published in Reinke et al. [32].

welas 2070HP) and a LC-PM-Sensor. The isokinetic probe sampling of the RI, as well as the inlet of the LC-PM-Sensor were directed against the flow direction. The LC-PM-Sensor is linked to a personal computer via a USB cable, enabling the storage and recording of data at 1 s. Subsequently, the aerosol enters the second process unit, the wet separator. The wet separator is a compact system comprising individual sub-units arranged in a vertical configuration, with the flow directed from the bottom to the top. The following sub-units are present: The initial stage is the washer unit. In the washer unit of the investigated wet separator, the aerosol first passes through a novel nozzle. The constricted cross-section induces suction, drawing the washing liquid into the nozzle through tubes immersed in the liquid reservoir. As the liquid enters the flow channel, it is dispersed by the gas stream, and the resulting three-phase mixture subsequently enters the vortex chamber. The vortex chamber is characterised by a high level of turbulence, which is generated by the whirlpool of washing liquid (water) that flows through it. As a consequence of the high turbulence, water droplets are generated. The droplets coalesce and subsequently break up, resulting in the collection of particles by the water droplets. Once particles have made contact with a droplet, it can be assumed that adhesion will occur [51]. For further information on particle separation mechanism in wet separators, the readers refer to [4]. The solubility of calcium carbonate in the washing liquid is negligible. Subsequently, a droplet separator is installed to facilitate the separation of the majority of droplets from the gas stream. The droplet separator comprises two distinct components: a deflection separator, which is designed to separate larger droplets due to inertial effects, and a coalescence droplet separator (wire mesh), which is intended to separate smaller droplets. Subsequently, the aerosol was characterised once more by a RI (Palas Promo 2000H with welas 2100HP) and multiple LC-PM-Sensors (2-5). The LC-PM-Sensors were connected to and powered by an Arduino microcontroller, which was then connected to a Raspberry Pi 4 microcomputer for the purpose of recording and saving data at a 1 s interval. The isokinetic probe sampling of the RI, as well as the inlet of the LC-PM-Sensors, were oriented at an angle of 90° relative to the flow direction. The probe sampling of the RI was connected to the sensor via a heated line (at 80 °C) with a length of 1 m, to remove any water from the aerosol stream. The RI was situated externally to the wet separator. Furthermore, the measurement channel of the RI was heated to 80 °C to prevent condensation on the sensor lenses. A final dry filter stage was implemented at the end of the wet separator to facilitate the separation of residual particles within the aerosol. The wet separator was equipped with a radial fan. The investigated process conditions

are listed in Table 3.2.

Table 3.2: *Process conditions of the wet separator.*

Parameter	Value	Condition / Description
Volume flow rate	4000 m ³ /h	In-line particle number concentration measurements
	6000 m ³ /h	In-line particle size distribution measurements
Particle mass flow rate	approx. 100 g/h	Constantly dispersed into the inlet pipe
Feed monitoring	–	By weighting module beneath the disperser

3.3 In-line particle number concentration measurements³

Following the analyzation of the measurement performance of LC-PM-Sensors under idealized conditions (see Chapter 2.7), one LC-PM-Sensor was installed within the inlet pipe of the wet separator to analyze the raw gas concentration of the process (see Chapter 3.3.1). Four LC-PM-Sensors were also installed inside the wet separator and above the droplet separator, for measuring local particle concentrations under high relative humidity conditions (70% rH) (see Chapter 3.3.2).

3.3.1 Particle concentration measurements in a raw gas channel of a wet separator

In ordner to to analyze the raw gas concentration of the process one LC-PM-Sensor was installed within the inlet pipe of the wet separator (see Figure 3.2). Figure 3.3 depicts the logarithmic particle number concentration measured at the inlet pipe, with data from the LC-PM-Sensor 2 presented in light green and data from the RI displayed in grey. In order to reduce the noise present in the RI data, a Savitzky-Golay filter (see Chapter 2.2.4) was applied, with the resulting smoothed data represented in black. Furthermore, the post-processed data from the LC-PM-Sensor are illustrated in green. For purposes of comparison, the maximum particle number concentration employed in deriving the correction

³Parts of this Chapter are published in Reinke et al. [32].

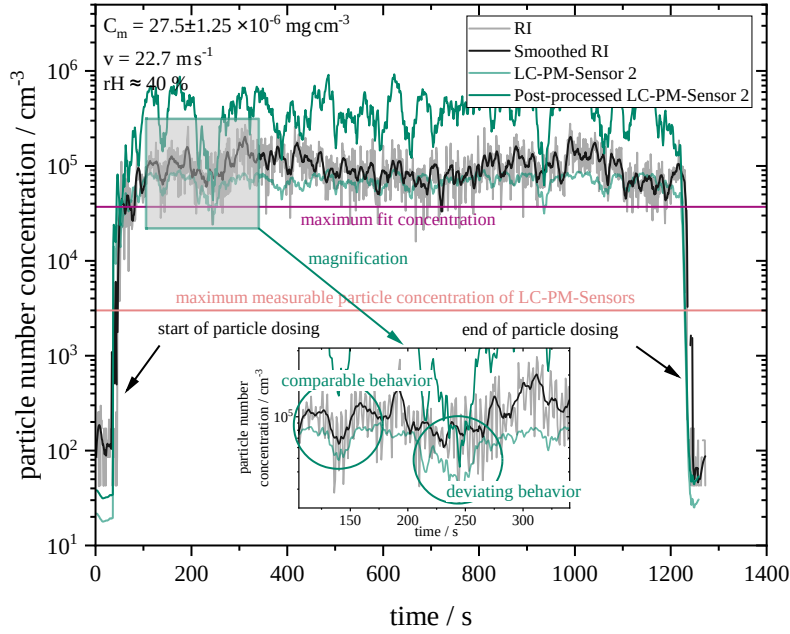


Figure 3.3: Particle number concentration measured by a RI and a LC-PM-Sensor over time in the raw gas channel.[32]

function is plotted in purple. A reference line indicates the maximum measurable particle number concentration of $3 \times 10^3 \text{ 1/cm}^3$ for the LC-PM-Sensors, as specified by the manufacturer [44]. The measurement conditions were as follows: The mass-based concentration, designated as C_m , exhibited a range of values between $27.5 \times 10^{-6} \text{ mg/cm}^3 \pm 1.25 \times 10^{-6} \text{ mg/cm}^3$, which corresponds to a particle mass flow rate at the brush disperser of approximately 100 g/h. The local flow velocity, designated as v , was determined to be 22.7 m/s, resulting from a volume flow of 4000 m³/h, as set at the wet separator. The relative humidity rH was maintained at 40 %. The beginning and end of particle dosing are indicated by the increase in particle number concentration at 35 s and the subsequent decrease at 1235 s. For the purpose of providing a more detailed view, an enlarged section of the plot, highlighting the particle number concentration measured by the LC-PM-Sensors and RIs, is provided for the time range of 106 s to 340 s. The maximum particle number concentration detected by the LC-PM-Sensor is approximately $8 \times 10^4 \text{ 1/cm}^3$, which is approximately 33 % higher than the measurements obtained under idealised conditions (see Chapter 2.7). Following the beginning of particle dosing at the brush disperser, both the RI and LC-

PM-Sensors registered an increase in particle number concentration. However, the particle number concentration curves exhibit the following differences. A comparison of the mean particle number concentrations over the investigated time period revealed that the RI measured approximately $8.9 \times 10^4 \text{ 1/cm}^3$, while the LC-PM-Sensor recorded around $6.4 \times 10^4 \text{ 1/cm}^3$, resulting in a 29 % deviation of the LC-PM-Sensor from the RI. On a short timescale, the LC-PM-Sensor's trend closely follows that of the RI (see Figure 3.3, enlarged section, 106 s to 176 s), although in other regions, deviations are observed (see Figure 3.3, enlarged section, 210 s to 280 s). The fluctuations observed in the particle number concentration measurements from both sensors can be attributed to the discontinuous operational behaviour of the brush disperser. These fluctuations also indicate the potential for mixing issues with the particles within the inlet pipe, which will be discussed further in Section 3.3.2. From these observations, it can be concluded that the LC-PM-Sensor is unable to accurately represent the mean particle number concentration level measured by the RI. Nevertheless, despite the particle number concentration measured by the RI being in excess of 20 times the maximum specified by the manufacturer for the LC-PM-Sensor, the LC-PM-Sensor is still capable of detecting elevated particle number concentration levels (up to $8 \times 10^4 \text{ 1/cm}^3$). Analysis of the post-processed data using the third-order polynomial regression correction function shows that applying this correction function to the LC-PM sensor data leads to an overestimation of the particle number concentration. This overestimation effect is more pronounced at higher particle number concentrations. For concentrations within the range of validity of the applied correction function (i.e., for $PC_N < 4 \times 10^4 \text{ 1/cm}^3$), the corrected values demonstrate a superior degree of agreement with the RI data. The overestimation of particle number concentration is primarily attributable to the extrapolation of the third-order polynomial correction function beyond its intended range. In conclusion, it can be stated that the correction function applied to the LC-PM-Sensor data is inadequate for accurately adjusting the LC-PM-Sensor measurements in the particle number concentration range exceeding $4 \times 10^4 \text{ 1/cm}^3$.

3.3.2 Particle concentration measurements in a wet separator

Following the initial measurement at the raw gas channel of the wet separator, the four previously investigated LC-PM-Sensors were installed within the wet separator (see Chapter 3.2), positioned above the droplet separator, for the purpose of measuring in-line particle concentration levels. Furthermore, the

sampling probe of the RI was positioned above LC-PM-Sensor 3 to ascertain whether the particle number concentrations measured by the LC-PM-Sensors are an accurate representation of the actual concentration levels. Figure 3.4 illustrates the particle number concentration over the course of the measurement period. The raw data from the RI are depicted in grey, while the smoothed

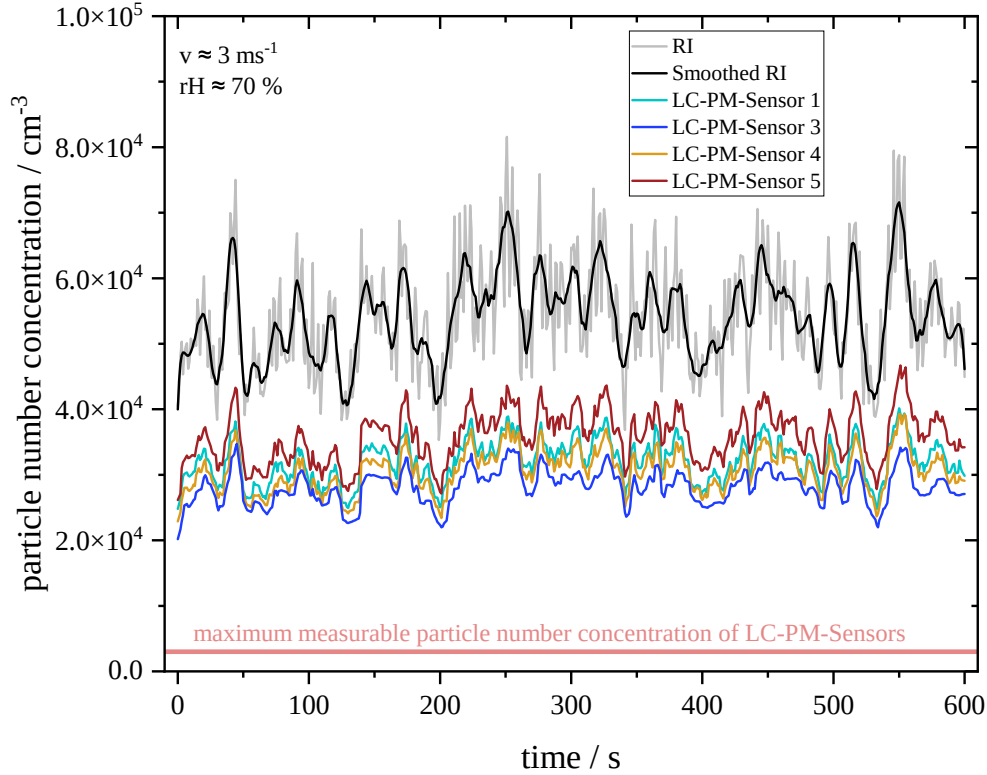


Figure 3.4: Particle number concentration measured by a RI and four LC-PM-Sensor over time above the droplet separator.[32]

RI data, processed using the Savitzky-Golay filter (see Chapter 2.2.4) [43] to reduce noise, are shown in black. The data from the various LC-PM-Sensors are presented in red, orange, turquoise, and green. The measurement conditions were as follows: the local flow velocity was approximately 3 m/s, and the relative humidity was approximately 70 %. The elevated relative humidity results from the measurement position downstream of the droplet separator. At this juncture, the aerosol had already traversed the vortex chamber (for further details, please refer to Chapter 3.2), resulting in an elevated relative humidity compared to the

measurement position at the raw gas channel. The fluctuations in particle number concentration observed by both the RI and LC-PM-Sensors are attributed to the pulsing operational behaviour of the brush disperser, which reflects short-term concentration variations (see Chapter 2.2.2). These distinctive fluctuations were consistently identified by all sensors, indicating that there are no significant time dependent particle concentration distribution issues above the droplet separator. It can therefore be inferred that a distribution of particles exists in the measurement region above the droplet separator which is constant in time. This indicates that any local concentration discrepancies observed in the raw gas are likely attributable to mixing concerns, as the short-term fluctuations induced by particle dosing remain discernible above the droplet separator. The stated time independence of the aerosol distribution after the droplet separator does not mean that no spatial differences in particle concentration, e.g. due to local discrepancies in particle separation efficiency of the upstream wire-mesh, exist. These spatial differences may lead to different measurement results in relation to a fixed-positioned reference sensor (which would require a concentration-independent constant scaling factor for each sensor position). The RI recorded a mean particle number concentration of $5.4 \times 10^4 \text{ 1/cm}^3$, while the LC-PM-Sensors reported mean values ranging from $2.8 \times 10^4 \text{ 1/cm}^3$ (for LC-PM-Sensor 3) to $3.6 \times 10^4 \text{ 1/cm}^3$ (for LC-PM-Sensor 5). The standard deviation of the measured particle number concentration for the RI was found to be 15 %, while the LC-PM-Sensors exhibited standard deviations ranging from 9 % to 11 %, indicating a similar degree of fluctuation relative to their respective mean values. The discrepancy between the LC-PM-Sensors and the RI mean value ranged from 34 % (for LC-PM-Sensor 5) to 48 % (for LC-PM-Sensor 3). An analysis of the time shift between the LC-PM-Sensor data and the RI data revealed no time shift, indicating that the local and global trends in particle number concentration measured by the LC-PM-Sensors closely followed those measured by the RI. In light of the aforementioned performance of the LC-PM-Sensors at this measurement position, namely their ability to capture both the actual particle number concentration level and the local and global trends, it is reasonable to apply the correction function derived from the measurements in Chapter 2.2.3. The diagram presented in Figure 3.5 illustrates the relationship between the particle number concentrations measured by the RI and the LC-PM-Sensors. The scatter plots compare the raw and post-processed data from each LC-PM-Sensor against the corresponding RI data, allowing for a visual assessment of the accuracy and consistency of the LC-PM-Sensor measurements relative to the RI. Each subplot corresponds to a different LC-PM-Sensor, with raw data depicted by one

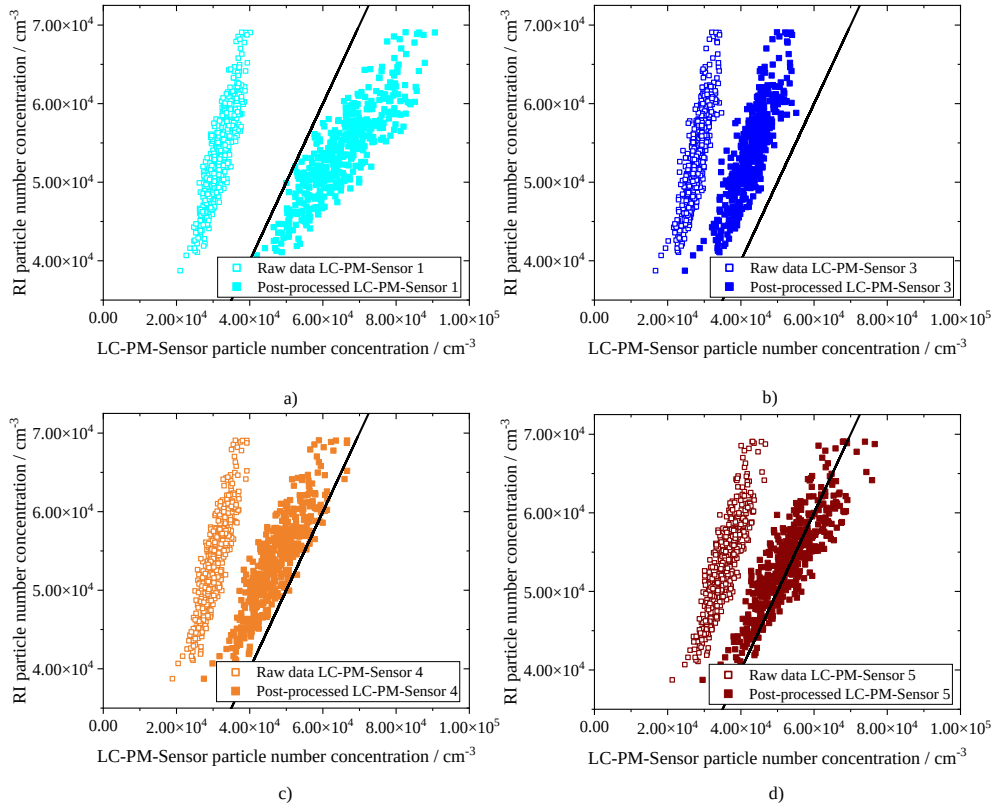


Figure 3.5: Scatter plots comparing the particle number concentrations measured by the RI and four LC-PM-Sensors. Each subplot (a-d) shows both raw and post-processed LC-PM-Sensor data, with a diagonal reference line indicating perfect agreement with the RI. [32]

set of markers and post-processed data by another, showing the effect of the applied correction function on the LC-PM-Sensor readings. The plots illustrate the degree of agreement between the corrected LC-PM-Sensor data and the RI data, particularly across different concentration ranges. The diagonal reference line represents the ideal scenario, whereby the LC-PM-Sensor would align with the RI, indicating no deviation. The extent to which the data points deviate from this line provides insight into the performance of the correction function and the accuracy of the LC-PM-Sensors under varying particle number concentrations. To further investigate the alignment between the corrected LC-PM-Sensor data and the RI data, the following Figure 3.6 examines the accuracy of the LC-PM-Sensors across different particle concentration ranges. The accuracy

was calculated as follows:

$$\text{Accuracy} = \frac{PC_N^{\text{LC-PM-Sensor}} - PC_N^{\text{RI}}}{PC_N^{\text{RI}}} \quad (3.2)$$

Figure 3.6 depicts the accuracy as a function of the RI's particle number con-

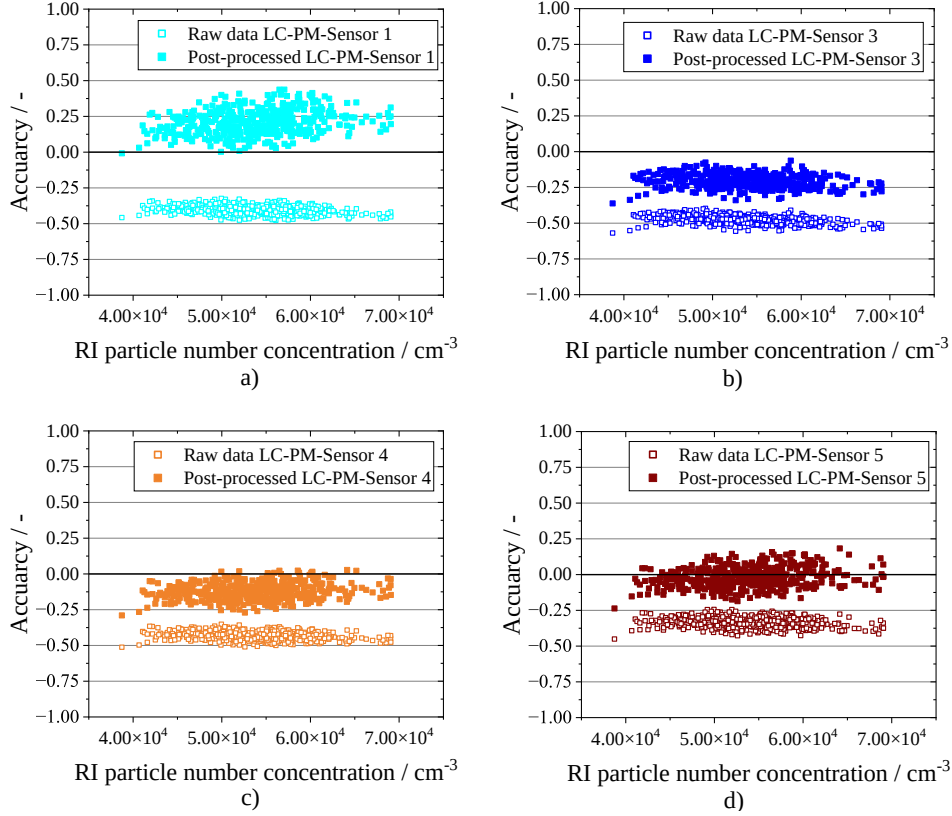


Figure 3.6: Accuracy comparison between RI and four LC-PM-Sensors (1, 3, 4, and 5) across different particle number concentrations. Each subplot (a-d) shows raw and post-processed data, with accuracy ranging from -1 to 1. [32]

centration for each LC-PM-Sensor. The relative error of the total particle number concentration, defined as the normalized difference between the LC-PM-Sensors and RI measurements with respect to the RI reference. The raw data and post-processed data for each LC-PM-Sensor are presented in separate subplots (a-d). The diagram illustrates the impact of particle concentration levels and the correction function on the accuracy of the LC-PM-Sensors. The subplots reveal trends in LC-PM-Sensor performance, indicating whether the applied correction

function enhances the sensor's accuracy or if deviations persist, particularly at higher concentrations. The behaviour of LC-PM-Sensors 1 to 5 exhibits notable discrepancies before and after post-processing, as depicted in the diagram. In the initial stage, the unprocessed data from these sensors display notable discrepancies from the reference values provided by the RI, particularly at elevated particle concentrations. This suggests that the LC-PM-Sensors are exhibiting a tendency towards an underestimation of particle counts. Consequently, the accuracy of these sensors in their uncorrected state is generally lower, particularly at concentration peaks. This reflects their limited capacity to accurately measure actual particle concentrations without correction. Following the application of the correction function, an improvement in the agreement between the LC-PM-Sensors and the RI was observed. In general, post-processing has a marked effect on the performance of the LC-PM-Sensors, aligning their data more closely with the RI's measurements and thereby providing a more accurate representation of particle concentrations. It can be observed that only LC-PM-Sensor 1 is overestimating the particle number concentration, whilst LC-PM-Sensors 3 and 4 are underestimating it, respectively. Conversely, LC-PM-Sensor 5 is demonstrating a perfect fit with the particle number concentration in accordance with the RI data. It is notable that there is a discrepancy of 1 % between the mean value of LC-PM-Sensor 5 and the mean value of the RI. The behaviour of LC-PM-Sensor 5 will be subjected to further analysis in the following section. Figure 3.8 depicts the particle number concentration over time of the smoothed RI data (obtained through the application of the Sovitzky-Golay filter (see Section 2.2.4) to the raw data) and the data of LC-PM-Sensor 5, which were also corrected through the use of a third-order polynomial correction function. The diagram excludes LC-PM-Sensors 1, 3 and 4, for the sake of clarity. It can be seen, that by applying the correction function of the LC-PM-Sensor 5 to the raw data of the LC-PM-Sensor 5, the data represents the particle number concentration values of the smoothed RI almost perfectly. Considering the other LC-PM-Sensor it can be analyzed that by scaling the measured particle number concentration by the following equation:

$$PC_{N,\text{scaled LC-PM-Sensor}} = \frac{\text{Mean value}_{\text{smoothed RI}}}{\text{Mean value}_{\text{post processed LC-PM-Sensor}}} \cdot PC_{N,\text{LC-PM-Sensor}} \quad (3.3)$$

The scaled particle number concentration of the LC-PM-Sensors then fits exactly the particle number concentrations measured by the RI. Therefore, the phenomena of over- or underestimating the particle number concentration is

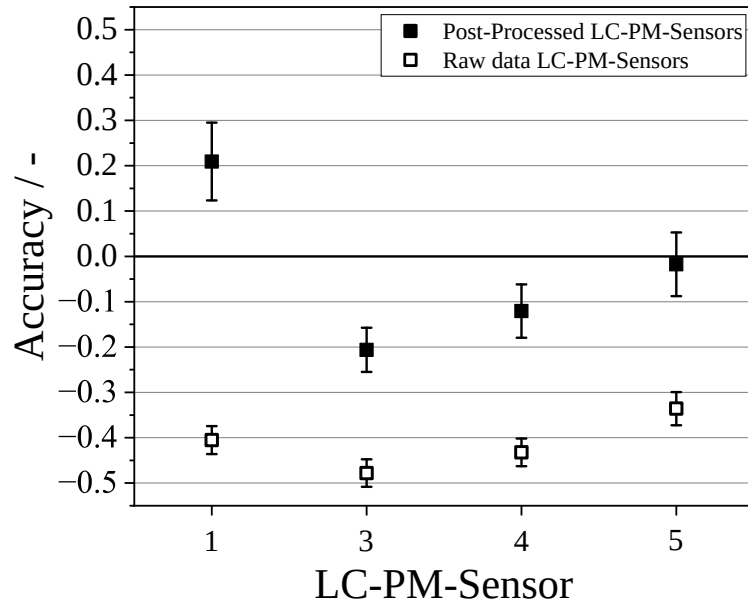


Figure 3.7: Comparison of mean accuracy between raw and post-processed data for LC-PM-Sensors 1 to 5. [32]

an scaling effect. Furthermore, the LC-PM-Sensors are able to represent the dynamic course of the particle number concentration within seconds. No time shift in the data is present. Therefore, it can be concluded, that the LC-PM-Sensor data correction function is capable to adapt the LC-PM-Sensor data in the presented particle concentration range ($2.0 \times 10^4 \text{ 1/cm}^3$ to $4.0 \times 10^4 \text{ 1/cm}^3$).

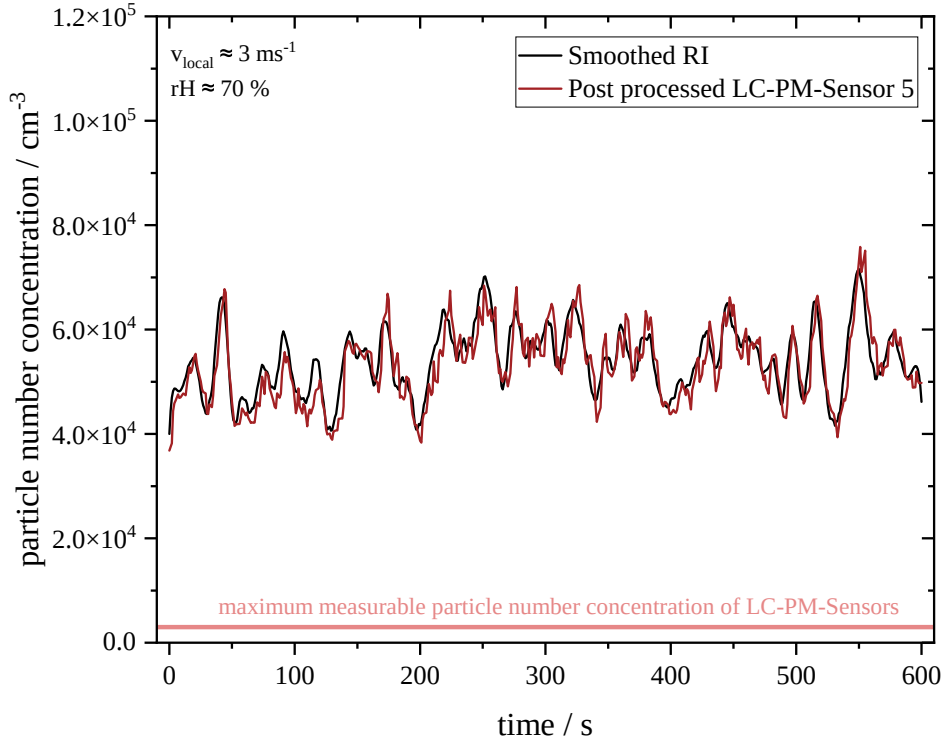


Figure 3.8: Particle number concentration measured by a RI and LC-PM-Sensor 5 over time above the droplet separator. [32]

3.4 Particle size distribution measurements in a wet separator

Following the initial measurements under idealized conditions which were used to derive the scaling factors (see Section 2.3), and the analyzation of the particle number concentration measurement performance in a wet separation test facility (see Section 3.3), the following chapter investigates their particle size distribution measurement performance above the droplet separator in the wet separator. Figure 3.9 illustrates the time-resolved particle number concentration measured by both the RI and four LC-PM-Sensors (LC-PM-Sensor 1, LC-PM-Sensor 3, LC-PM-Sensor 4, and LC-PM-Sensor 5) across individual particle size fractions: $\Delta PC_{N,PM_{0.5}}$, $\Delta PC_{N,PM_{1.0}}$, and $\Delta PC_{N,PM_{2.5}}$. The data from the RI are smoothed (data pre-processing according to Sec. 2.2.4), providing a refer-

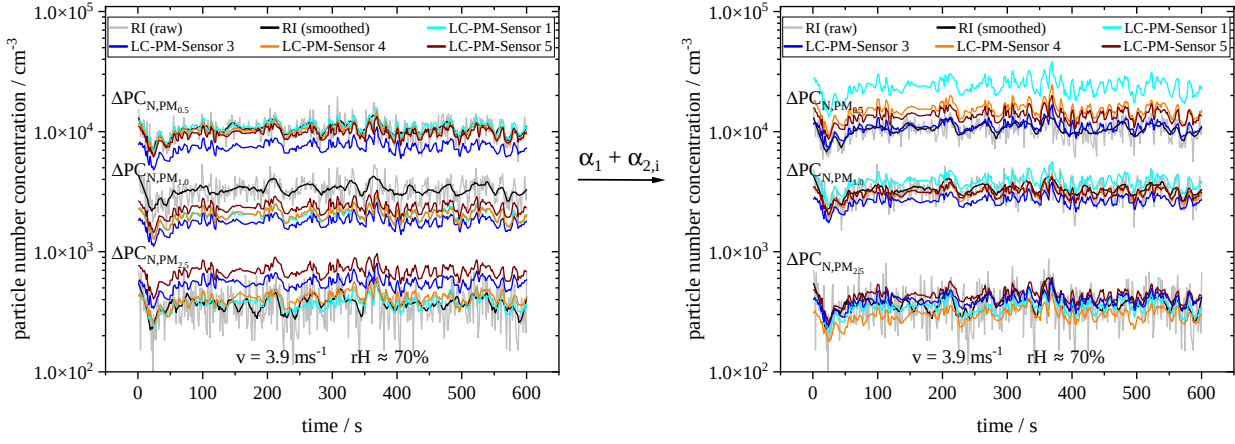


Figure 3.9: Left: Particle number concentration of each class measured by four LC-PM-Sensors (raw data) and one RI over time above the droplet separator. Right: Particle number concentration of each class measured by the same four LC-PM-Sensors after applying both correction factors α_1 and $\alpha_{2,i}$ from the measurement chamber, and the same RI over time above the droplet separator.

ence curve for comparison with the LC-PM-Sensor data. Each LC-PM-Sensor's performance is plotted separately, highlighting discrepancies and similarities in particle number concentration measurements over time. The time-resolved particle number concentration measurements across multiple particle size fractions allow for the evaluation of the LC-PM-Sensor's ability to accurately classify particle sizes and, consequently, provide a PSD. The analysis of the particle number concentration curves presented in Figure 3.9 (left) for the $\Delta PC_{N,PM_{0.5}}$ fraction reveals that this size fraction constitutes the largest proportion of the measured aerosol, followed by the $\Delta PC_{N,PM_{1.0}}$ and $\Delta PC_{N,PM_{2.5}}$ fractions. This is attributed to the high number of sub-micron particles in the aerosol (see Sec. 2.2.2). Across all particle size classes, the LC-PM-Sensors maintain their ability to reproduce the local trends of the particle concentration curve after the data post-processing (Figure 3.9 right). Following the analysis of both global and local trends after the application of the scaling factors α_1 and $\alpha_{2,i}$, the accuracy of the post-processed data is evaluated. This assessment focuses on quantifying the improvement in measurement precision for each particle size fraction after the scaling corrections have been applied. Figure 3.10 presents scatter plots comparing particle number concentrations measured by the RI and four LC-PM-Sensors across three particle size fractions: $\Delta PC_{N,PM_{0.5}}$, $\Delta PC_{N,PM_{1.0}}$, and

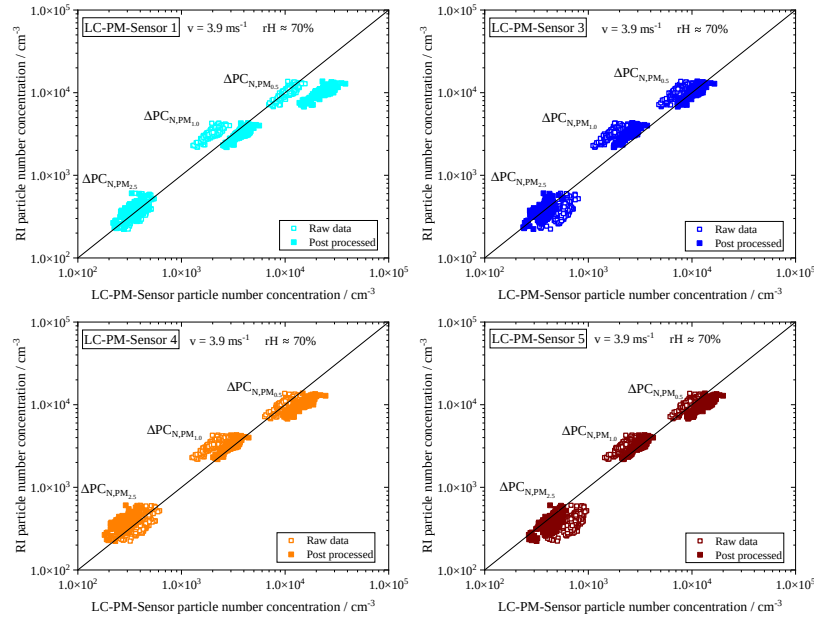


Figure 3.10: Scatter plots comparing the particle number concentrations measured by the RI sensor and the four LC-PM-Sensors.

$\Delta PC_{N,PM_{2.5}}$. The scatter plots provide a direct comparison of the measurement performance between the LC-PM-Sensors and RIs, with data points representing α_1 & $\alpha_{2,i}$ -corrected and raw data values. The black line represents the reference line indicating perfect alignment between the LC-PM-Sensor measurements and the RI data. The performance of LC-PM-Sensors across different particle size fractions ($\Delta PC_{N,PM_{0.5}}$, $\Delta PC_{N,PM_{1.0}}$, and $\Delta PC_{N,PM_{2.5}}$) revealed post-processing trends. For the $\Delta PC_{N,PM_{0.5}}$ fraction, all LC-PM-Sensors (except for LC-PM-Sensor 3 which underestimated the particle concentration level) measured the actual particle concentration level prior to post-processing. The $\Delta PC_{N,PM_{1.0}}$ fraction was underestimated by every LC-PM-Sensor. The $\Delta PC_{N,PM_{2.5}}$ fraction was overestimated by LC-PM-Sensors 3 and 5, while LC-PM-Sensors 1 and 4 presented the actual particle concentration. After applying the scaling factors α_1 and $\alpha_{2,0.5}$ to the $\Delta PC_{N,PM_{0.5}}$ fraction, LC-PM-Sensor 3 data points better align with the RI, but slightly overestimated the particle concentration. LC-PM-Sensors 1, 4, and 5 overestimated the actual particle concentration significantly, as expected. Moreover, it is noteworthy that the $\Delta PC_{N,PM_{0.5}}$ fraction measured by the LC-PM-Sensors (with the exception of LC-PM-Sensor 3) aligns well with the RI data prior to post-processing, indicating good measurement performance of

the LC-PM-Sensors within this particle size range. Analyzing the post-processed $\Delta PC_{N,PM_{1,0}}$ fraction, every LC-PM-Sensor now presented the actual particle concentration range. For the $\Delta PC_{N,PM_{2,5}}$ fraction, all LC-PM-Sensors were shifted to lower particle concentration values following the post-processing, and therefore every LC-PM-Sensor closely approximated the RI measurements. Qualitatively, coincidence effects are observable; however, their quantitative influence cannot be directly identified, as additional effects such as deviating class assignments may occur alongside coincidence effects. The relative error prior and post the

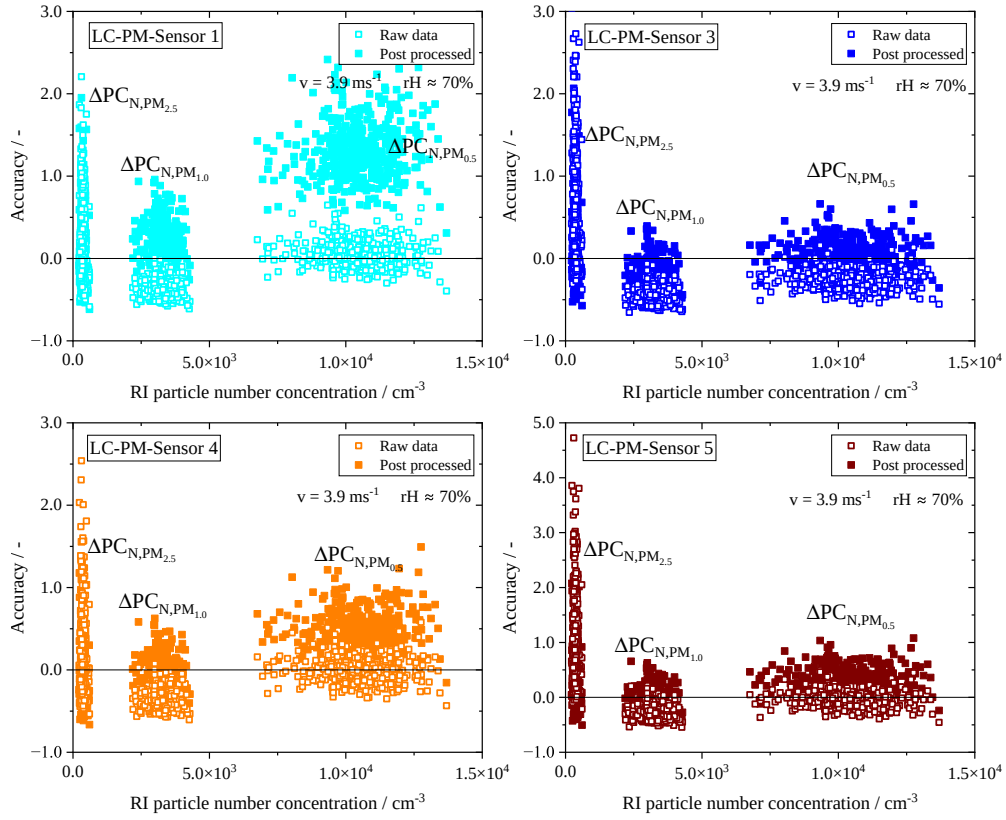


Figure 3.11: Raw and post-processed (using sensor-specific $\alpha_{2,i}$ -values) accuracy levels plotted against particle number concentrations (measured in $1/\text{cm}^3$) for different size fractions ($\Delta PC_{N,PM_{0,5}}$, $\Delta PC_{N,PM_{1,0}}$, $\Delta PC_{N,PM_{2,5}}$) and LC-PM-Sensor configurations (Sensors 1, 3, 4, and 5).

application of the scaling factors are given in Figure 3.11 for each sensor and each size fraction across the particle number concentration in the respective size class measured by the RI. Based on the aforementioned results, a fundamen-

tal question emerges regarding the disparity in LC-PM-Sensor measurement performance between the measurement chamber and the wet separator. These disparities result in correction functions that, while effective for total particle number concentration adjustment [32], demonstrate only partial efficacy in correcting individual size fractions. Figure 3.12 illustrates the cumulative particle size distribution (Q_0) as a function of particle size at different environments for both RI and LC-PM-Sensors. The mean PSD measured in the measurement chamber is depicted in grey, while the wet separator measurements are shown in green. A higher proportion of submicron particles was detected at the wet separator by both RI and LC-PM-Sensors. This results in an increased fraction of submicron particles detectable across all LC-PM-Sensors (see Figure 3.10). This elevated proportion of submicron particles can be attributed to the separation characteristics of the wet separator and its enhanced capability to separate micron-sized particles [4]. Consequently, while the measured $\Delta PM_{0.5}$ fraction appears overestimated following the application of scaling factors, the LC-PM-Sensors actually demonstrate good measurement performance for particles in the class $0.3 \mu\text{m}$ to $0.5 \mu\text{m}$ compared to the measurement chamber. Notably, the $\Delta PM_{0.5}$ fraction alone exceeds the specified maximum particle concentration of 3000 1/cm^3 by an order of magnitude ($\approx 1 \times 10^4 \text{ 1/cm}^3$).

3.4.1 Generalized polynomial correction approach for measuring particle size distributions

Based on the findings obtained with the previous approaches, a generalized correction approach was investigated (see Section 2.6.1). Comparative visualizations for the data using the generalized $\alpha_{2,i}$ values (similar to those already shown for the sensor-specific $\alpha_{2,i}$ approach) were generated to illustrate the generalized correction's efficacy in Figure C.2 presenting the uncorrected and corrected particle number concentrations for the specified size classes, and Figure C.3 depicting the corresponding relative errors. A comparative analysis was conducted to assess the performance of the generalized polynomials against sensor-specific polynomial corrections for $\alpha_{2,i}$. Upon quantitative analysis of the data, no significant differences were observed between the sensor-specific polynomial approach for correction and the averaged polynomial approach. The empirical findings suggest a streamlined approach to sensor calibration wherein the total number concentration correction factor α_1 necessitates sensor-specific determination, while for individual size class corrections ($\Delta PC_{N,PM_{0.5}}$, $\Delta PC_{N,PM_{1.0}}$, and $\Delta PC_{N,PM_{2.5}}$), the generalized polynomials presented in Table 2.6

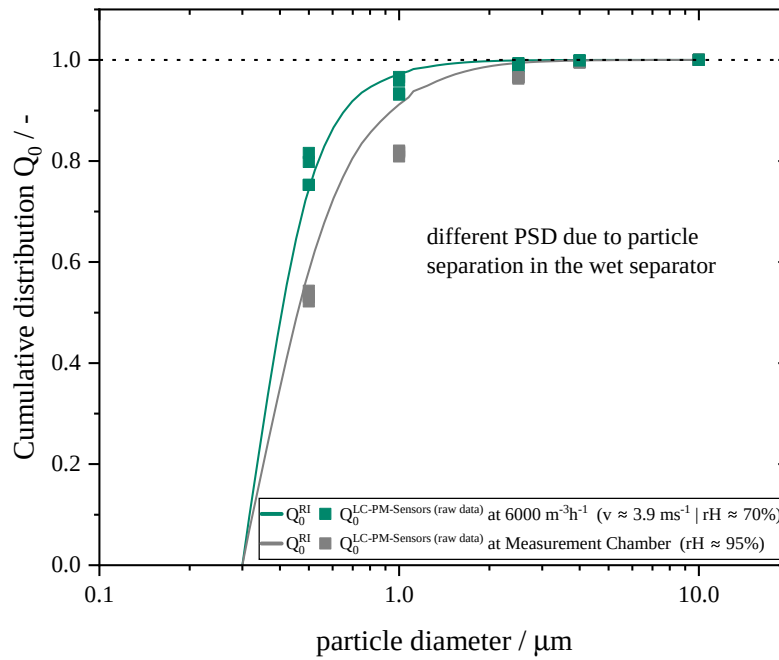


Figure 3.12: Number based particle size distribution Q_0 measured by the RI (lines) and four LC-PM-Sensors (squares) in the measurement chamber (grey) and in the wet separator (green).

can be applied universally.

3.5 Conclusion

Following the measurements under idealised laboratory conditions, the LC-PM-Sensors were installed at two positions within the wet separation test facility to evaluate their performance under process conditions. At the raw-gas inlet, the LC-PM-Sensor substantially underestimated the particle number concentration, measuring approximately $6.4 \times 10^4 \text{ 1/cm}^3$ compared with $8.9 \times 10^4 \text{ 1/cm}^3$ recorded by the RI. Both concentrations exceeded the range used to establish the third-order polynomial correction function, and extrapolation beyond its upper limit of approximately $4 \times 10^4 \text{ 1/cm}^3$ led to significant overestimation when the correction was applied. In contrast, at the second position above the droplet separator, four LC-PM-Sensors measured particle number concentrations within the correction function's validity range. Their deviations relative to

the RI were 34–48%, and further decreased to 1–20% after applying the polynomial correction. LC-PM-Sensor 5 showed the closest agreement, with a deviation of only 1%, accurately reproducing both mean and dynamic trends. Residual deviations were attributed to sensor-specific constant scaling errors, which could be compensated using individual scaling factors. Overall, the LC-PM-Sensors demonstrated an in-line measurement capability under real operating conditions that exceeded their specified operating limits by at least one order of magnitude.

The extended evaluation within the wet separator also showed that the LC-PM-Sensors were capable of tracking local particle concentration trends across all examined particle size classes, even when operating beyond their nominal limits. Prior to applying the scaling factors α_1 and $\alpha_{2,i}$, most sensors correctly captured the $\Delta PC_{N,PM_{0.5}}$ fraction, except for LC-PM-Sensor 3, which underestimated this class. The wet separator generated a substantially larger proportion of submicron particles than the measurement chamber, likely due to enhanced removal of larger particles, resulting in $\Delta PC_{N,PM_{0.5}}$ concentrations exceeding the specified maximum of 3000 1/cm³ by an order of magnitude. The $\Delta PC_{N,PM_{1.0}}$ fraction was generally underestimated, whereas $\Delta PC_{N,PM_{2.5}}$ was overestimated by sensors 3 and 5. After applying the scaling factors, all sensors overestimated the $\Delta PC_{N,PM_{0.5}}$ fraction but showed strong alignment with the RI for $\Delta PC_{N,PM_{1.0}}$. For $\Delta PC_{N,PM_{2.5}}$, all LC-PM-Sensors shifted toward lower values, improving agreement with the RI. These results aligned with previous findings, confirming that LC-PM-Sensors generally performed best in the 0.3 μm to 0.5 μm size range. However, accuracy within this class declined after applying the scaling factors (with the exception of LC-PM-Sensor 3), indicating that the effectiveness of such corrections depended on both the particle size distribution and sensor specific characteristics.

4

Application of Low-Cost PM-Sensors for Emission Characterization of a Cartridge Filter System

The objective of this chapter is to assess the suitability of LC-PM-Sensors for implementation in industrial dust collection systems, with the aim of extracting operational information from measured emission data. The focus lies on determining whether LC-PM-Sensors provide the temporal and quantitative resolution required to monitor and evaluate the operating state of modular extraction units. In this chapter, no correction of the LC-PM-Sensors data is performed, in order to assess their applicability in the investigated system without prior adjustment.

The analysis is based on model equations derived from empirical correlations available in the literature to describe a cartridge filter system. These equations provide a preliminary description of the emission behavior, and the power demand as a function of the operating parameters. They serve as a framework for predicting operating states and identifying energy and emission optimized operating conditions.

LC-PM-Sensor measurements are subsequently used to adjust and validate the emission-related components of these model equations. Emission profiles of individual filtration cycles are compared with the corresponding model predictions to quantify deviations and assess model accuracy. This approach enables

an evaluation of the extent to which LC-PM-Sensors can support monitoring, model refinement, and predictive operation of industrial dust collection systems.

4.1 Fundamentals of Surface Filtration

Filtering separators can be classified according to their operating principle, structural design and mode of operating into three groups: depth or storage filters, surface or cleaning filters and bulk bed filters [4]. The cartridge filters used in this work belong to the class of surface filters. The following section therefore focuses on the fundamentals of surface filtration and specifically on cartridge filters. Fundamental information on depth filters and bulk bed filters are presented in [4]. The three principal fields of application of surface or cleaning filters are emission reduction, product recovery and process gas purification [52]. Surface or cleaning filters are mainly employed at high dust concentrations on the order of several g/m^3 and in industrial processes with continuous operation. The filter medium consists either of coherent collectors such as needle felt, fleece or woven fabrics or of a porous continuous phase such as sintered ceramics metals or polymers. The porosity ϵ of the filter medium typically ranges from 70% to 90% and the filtration velocity w_f lies between 0.5 cm/s to 5 cm/s. Due to the pleated structure of the medium, cartridge filters offer a large filtration area at a small footprint. [4]

4.1.1 Particle Separation in Surface Filtration

Phases of Surface Filtration

In general, five phases of cleaning filters can be distinguished: the initial condition of the new filter medium, the phase during which particles begin to penetrate and deposit within the medium, followed by the clogging stage, and finally the formation of the filter cake, which is subsequently removed during cleaning. In the clogging phase particles penetrate the filter medium and are retained within its pore structure. As particle loading increases the pore entrances on the inflow side become locally obstructed which is referred to as clogging. This stage is followed by the formation of a filter cake on the surface of the filter medium. During this phase particles accumulate on the outer layer of the cake which causes progressive cake growth. The increasing cake thickness results in a continuous rise in pressure drop Δp . Regeneration of the filter is therefore performed either at predefined intervals or once a

maximum allowable pressure drop is exceeded. A distinction is made between offline regeneration where the raw gas flow is interrupted during cleaning and online regeneration where filtration continues throughout the process. In this work an online regeneration strategy is applied by introducing a short pulse of compressed air in reverse flow direction. [4]

Separation Mechanisms in Surface Filtration

At the beginning of operation the filter medium is unused and its pore structure unfilled. During the clogging phase particles are deposited inside the medium. For a particle to be retained within the medium it must reach a collector element such as a fiber and subsequently adhere to it. Several mechanisms govern particle transport toward the collector [4, 53]. Small particles undergo random displacements caused by Brownian motion which increases the probability of impingement on a collector. This diffusional deposition mechanism is most relevant for particle sizes $\leq 0.1 \dots 0.5 \mu\text{m}$ and for inflow velocities $u < 0.1 \text{ m/s}$. Another mechanism is interception where particles follow the streamlines of the gas flow but contact the collector due to their finite diameter. Although interception does not involve an active transport toward the fiber it still leads to deposition when the geometric proximity is sufficient. Larger particles have sufficient inertia to deviate from the gas streamlines when passing around a fiber which results in impact on the collector surface. This inertial deposition mechanism becomes dominant for particles larger than $1 \mu\text{m}$ [4, 53]. After clogging has advanced, deposition occurs predominantly on the forming filter cake. In this stage separation is largely governed by the sieving effect in which particles are retained at the cake surface. Increasing cake thickness enhances separation efficiency while simultaneously causing an increase in pressure drop [4, 54].

4.2 Particle Emissions and Power Demand of Surface Filtration

4.2.1 Particle Emissions in Surface Filtration

Leith and First [55] describe three main mechanisms responsible for particle emissions during surface filtration. The first mechanism, known as direct penetration ("straight through"), occurs when particles penetrate the filter medium immediately following regeneration. The second mechanism arises at high

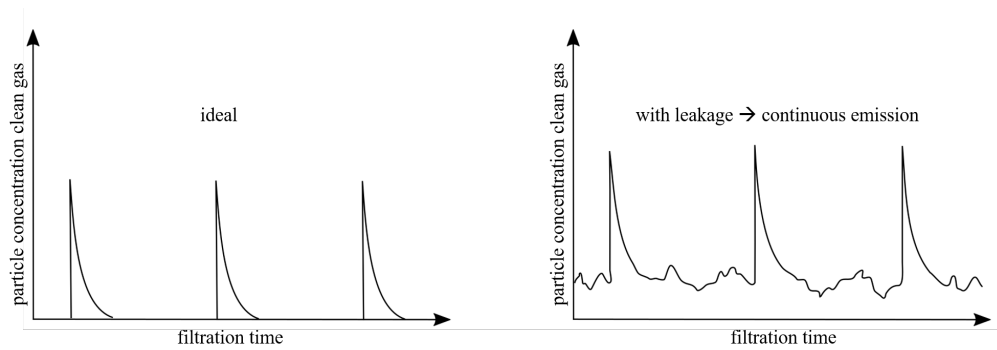


Figure 4.1: Schematic representation of the typical temporal progression of particle concentration on the clean gas side without continuous emission (left) and with continuous emission (right). According to Kurtz et al. [58].

filter inflow velocities or during regeneration, causing stretching and deformation of the filter medium. This deformation can dislodge particles previously embedded in the filter medium, allowing them to migrate to the clean gas side ("seepage"). The third mechanism refers to particle penetration through small holes ("pinholes") in the dust cake, which develop due to fabric and structural imperfections or damage to the filter medium [55]. Binnig et al. [56] demonstrate that direct penetration represents the primary cause of particle emissions during surface filtration. Figure 4.1 schematically illustrates the typical temporal progression of particle concentration on the clean gas side after the clogging phase, depicting scenarios without continuous emission (left) and with continuous emission (right). The emission peaks result from the direct penetration mechanism immediately after regeneration. To achieve a reduced emission level, it is desirable to extend the cycle time, which, in pressure-controlled regeneration, can be accomplished by permitting a higher maximum pressure loss. However, this higher differential pressure leads to increased energy consumption. The magnitude and duration of emission peaks depend significantly on the dust and filter medium characteristics, operational parameters, and especially the regeneration method and its intensity [4, 57]. Furthermore, continuous emissions throughout the entire filtration period (see Figure 4.1, right side) may occur for various reasons. Incorrect installation of filter elements or weak points resulting from the manufacturing process (e.g., seams [29]) can contribute substantially to overall emissions. Additionally, damage to the filter medium caused by mechanical or thermal stress may result in leaks. [58–60] The outlet concentration downstream of a filter can be expressed as

$$c_{out}(t) = c_{in}(t) \cdot (1 - E(t)), \quad (4.1)$$

where $E(t)$ is the time-dependent separation efficiency, $c_{out}(t)$ the outlet concentration, and $c_{in}(t)$ the inlet concentration. It is assumed that the separation efficiency is initially low immediately after regeneration (E_{min}) and then increases exponentially towards a maximum value E_D . This behavior is described by a first-order exponential function:

$$E(t) = E_D - (E_D - E_{min}) \exp\left(-\frac{t}{t_{reg}}\right). \quad (4.2)$$

Accordingly, the outlet concentration can be written as

$$c_{out}(t) = c_{in}(t) \cdot \left(1 - \left(E_D - (E_D - E_{min}) \cdot e^{-\frac{t}{t_{reg}}}\right)\right). \quad (4.3)$$

Here, t is the time after a regeneration pulse, and t_{reg} the characteristic time after which the emission has decayed to $1/e$ of its initial value. E_D denotes the maximum separation efficiency during filtration, while E_{min} represents the efficiency during the regeneration pulse. The only variable parameter for calculating the outlet concentration c_{out} is the inlet concentration c_{in} , which is defined as

$$c_{in} = \frac{\dot{m}}{\dot{V}}, \quad (4.4)$$

where $\dot{m}$ is the dust mass flow and $\dot{V}$ the gas volumetric flow rate. In this model, an increase in inlet concentration raises both the baseline emission and the magnitude and width of the emission peak. The peak width is primarily governed by the parameter t_{reg} . Higher values of t_{reg} lead to broader peaks and thus greater overall emissions. The maximum separation efficiency E_D controls the level of baseline emissions, whereas the minimum efficiency E_{min} determines the peak height.

4.2.2 Power demand of surface filters

Surface filters with jet-pulse regeneration during online operation primarily require energy for compressed air (approximately 15%) and for the fan (approximately 85%) [61]. According to Höflinger and Laminger [62], the power demand of surface filters can be described by

$$P_{overall} = P_{fan} + P_{regeneration} \quad (4.5)$$

with,

$$P_{\text{fan}} = \Delta \bar{p}_{\text{filter}} \cdot \dot{V} \quad (4.6)$$

and

$$P_{\text{regeneration}} = \frac{\Delta p_{\text{tank}} \cdot V_{\text{tank}}}{\Delta t_{\text{cycle}}}. \quad (4.7)$$

The total power demand P_{overall} results from the sum of the power requirement of the fan P_{fan} and the power requirement for regeneration $P_{\text{regeneration}}$. The power demand for the fan is calculated from the average pressure drop $\Delta \bar{p}_{\text{filter}}$ across the filter cartridges and the volumetric flow rate $\dot{V}$. The power required for regeneration depends on the tank pressure difference Δp_{tank} , the tank volume V_{tank} , and the cycle time Δt_{cycle} , which is the time interval between two regeneration events [62]. The differential pressure between the raw and clean gas sides, Δp_{filter} , is calculated using the so called filter equation for a single filter element i , as a function of the specific cake resistance $K_{\text{cake},i}$, the specific medium resistance $K_{\text{medium},i}$, the deposited dust mass W_i , and the face velocity $w_{f,i}$:

$$\Delta p_{\text{filter}} = K_{\text{medium}} \cdot w_{f,i} + K_{\text{cake}} \cdot W_i \cdot w_{f,i}. \quad (4.8)$$

This equation assumes homogeneous flow through the filter cartridge, constant process parameters, an incompressible dust cake, and negligible housing pressure losses. For constant face velocity (e.g., at a single filter element) and 100% separation efficiency, the pressure drop increases linearly with the deposited dust mass. For a dedusting system with two filter cartridges (which are cleaned alternately), their dust loads differ, and each cartridge exhibits an individual, time-dependent resistance constant K_i :

$$K_i = K_{\text{medium},i} + K_{\text{cake},i} \cdot W_i. \quad (4.9)$$

From the individual constants K_i , the overall resistance constant K_{tot} for multiple filter cartridges is calculated as

$$K_{\text{tot}} = \frac{n}{\sum_{i=1}^n \frac{1}{K_i}}. \quad (4.10)$$

For two cartridges, the differential pressure becomes

$$\Delta p_{\text{filter}} = K_{\text{tot}} \cdot w_f = \frac{2}{\frac{1}{K_1} + \frac{1}{K_2}} \cdot w_f, \quad (4.11)$$

with K_1 and K_2 denoting the resistance constants of the two cartridges. Since the pressure drop Δp_{filter} is identical across both cartridges, the volumetric flow through each element i is given by

$$\dot{V}_i = \frac{\Delta p_{\text{filter}} \cdot A_i}{K_i}. \quad (4.12)$$

Filtration leads to dust cake growth on the filter medium until regeneration removes it. Owing to the very high separation efficiency of surface filters, a constant separation efficiency of 100% is assumed. The time-dependent dust mass per filter area is then calculated as

$$W_i(t + \Delta t) = W_i(t) + \frac{\dot{V}_i}{A_i} \cdot c_{\text{rawgas}} \cdot \Delta t, \quad (4.13)$$

with $W_i(t)$ denoting the previously deposited mass and c_{rawgas} the raw gas concentration. Regeneration is triggered either after a predefined time interval or when a set differential pressure is exceeded, and it is assumed to fully remove the dust cake:

$$W_i(t) \rightarrow 0. \quad (4.14)$$

Using Equations 4.8–4.14, surface filter systems can be modeled in a time-resolved manner [4, 63, 64]. Figure 4.2 qualitatively illustrates the progression of total, fan, and regeneration power over the cycle time. The power demand

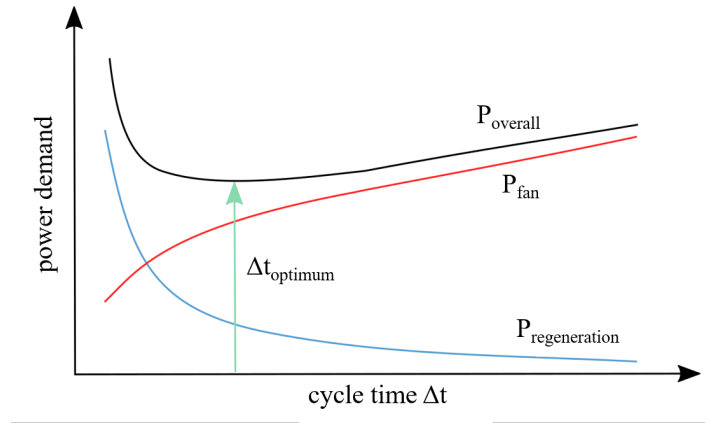


Figure 4.2: Qualitative representation of power demand as a function of cycle time. Adapted from Bächler et al. [63].

of the fan increases with rising cycle time, as the pressure drop caused by the

growing filter cake continuously increases. In contrast, the power requirement for regeneration increases with decreasing cycle time due to the more frequent withdrawal of compressed air. From these two contributions, the total power demand can be calculated, and the energetically optimal cycle time $\Delta t_{\text{optimum}}$ can be determined [10].

4.3 Experimental Setup

This chapter presents the experimental setup designed to evaluate the capability of LC-PM-Sensors in validating empirical models that describe particle separation characteristics. The description includes the configuration of the test facility, the measurement equipment, and the procedures applied to ensure reliable data acquisition. Figure 4.3 shows a photograph of the experimental setup used for the cartridge filter system tests. On the left-hand side, the employed dust separation unit, the cartridge filter system, is depicted. These units are designed for the extraction of dry, free-flowing dusts and chips. Depending on the configuration, the cartridge filter system can also be used for carcinogenic, or explosive dusts as well as in applications with sparks. The cartridge filter system has a length of 1.63 m, a width of 0.84 m, and a height of 1.68 m [65]. The particle feeder and disperser Dust Feeder NDF100-3FI by FilTEq GmbH is

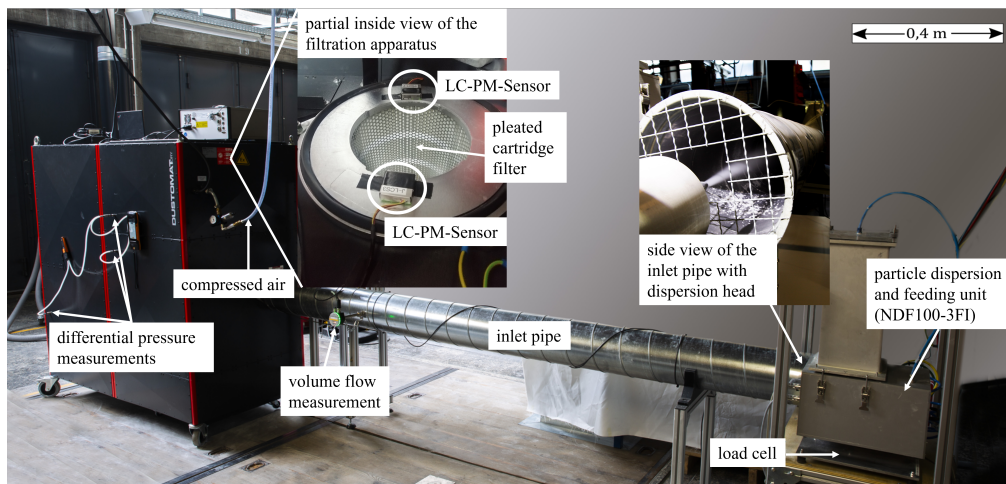


Figure 4.3: Photography of the experimental setup of the used pleated cartridge filter apparatus. Including partial inside view of the filtration apparatus for the measuring points of the LC-PM-Sensor.

shown on the right-hand side. The dust feeder used in this study employs the same base unit for control but differs in the dispersion mechanism, which is based on compressed air rather than the brush system (see Section 2.2.2). The 3FI feeder was selected to generate higher mass flows of up to 3 kg/h. The test aerosol exits the nozzle of the disperser into a 3 m inlet pipe. At a distance of 2.25 m from the nozzle, the flow velocity is measured in the pipe centerline. At the inlet to the cartridge filter system, the raw gas first passes a deflection plate. The gas then flows through the filter cartridges from the outside to the inside, where particle separation occurs. The cartridge filter system used here contains two filter cartridges. Figure 4.4 shows a photograph of a brand new filter cartridge. The specifications of the investigated cartridges are listed in Table 4.1.



Figure 4.4: Photograph of the investigated filter cartridge.

The cartridges are manufactured entirely from polyester spunbond nonwoven fabric. Each cartridge provides a filter area of 2.5 m^2 . The air permeability of the unused filter medium is specified as $5040 \text{ m}^3/(\text{m}^2 \text{ h})$ at a pressure drop of 200 Pa. Filter cartridges are regenerated alternately by compressed air pulses. The compressed air is released via a nozzle from a pressurized tank, which is supplied through a connection to the plant air system. The detached dust settles in a disposal container at the base of the filter unit. The container must be checked and emptied before each measurement. The differential pressure is

Table 4.1: *Product properties of the filter cartridges used in this study [66].*

Cartridge height	300 mm
Nominal diameter	324 mm
Filter area	2.5 m ²
Number of pleats	86
Fiber material	Polyester spunbond nonwoven
Basis weight	180 g/m ²
Air permeability at 200 Pa	5040 m ³ /(m ² h)

measured between the raw gas and clean gas compartments of the cartridge filter system. The clean gas compartment houses the instrumentation used to detect emissions downstream of the filter cartridges. Figure 4.3 shows also a partial inside view in the filtration apparatus to indicate the positioning of the used two LC-PM-Sensors (SPS30, Sensirion AG). Downstream of the filter cartridges, a secondary depth filter captures residual particles to prevent the release into the environment. After passing this filter, the cleaned air exits the cartridge filter system through the outlet openings of the fan unit into the surrounding area. The fan frequency (and therefore the volumetric flow rate) and cycle time were set via the control unit of the cartridge filter system. The adjustable cycle time corresponds to the interval between two compressed-air cleanings of the filter cartridges. The circulation time denotes the interval between two regenerations of the same cartridge. Since the cartridge filter system contains two filter cartridges and cleaning is performed alternately, the circulation time equals twice the cycle time. Prior to each experiment, data acquisition was initiated for the LC-PM-Sensors, the flow sensor, and the differential pressure sensor. Dust mass flow, differential pressure, and flow velocity were recorded at 1 Hz. The dust mass flow was controlled by the feed voltage of the dosing screw and set to the minimum (1.5 V) and maximum (9.9 V) levels. The dosing and dispersion unit was placed on a loading cell to determine the dosed particle mass, from which the mean dust mass flow was calculated. For measuring the pressure drop, a piezoresistive pressure sensor manufactured by Testo SE & Co. KGaA was used (testo 400 with an additional testo 510i sensor). The measurement interval was 1 Hz, and data storage was performed locally on the device.

4.4 Parametrisation of the model equations

4.4.1 Power demand of jet-pulsed cleaned cartridge filter system

This chapter presents the experimental results regarding the parametrisation of the model equations to describe the power demand of the cartridge filter system. The corresponding experimental setup is described in Chapter 4.3. The total power demand of the system is calculated according to Equation 4.5 as the sum of the fan power P_{fan} and the power required for compressed air supply during regeneration $P_{\text{regeneration}}$. The fan power is determined by Equation 4.6 as the product of the mean pressure drop across the filter cartridges $\Delta \bar{p}_{\text{filter}}$ and the volumetric flow rate $\dot{V}$. The mean pressure drop $\Delta \bar{p}_{\text{filter}}$ can be derived from the filter equation 4.11, which depends on the filter medium resistance K_{medium} , the filter cake resistance K_{cake} , the deposited dust mass per area W_i , and the face velocity w_i . Consequently, both K_{medium} and K_{cake} must be determined in order to adapt the power demand of the cartridge filter system (see Chapters 4.4.1.1 and 4.4.1.2). In addition, the model equations require knowledge of the tank volume V_{tank} of the cartridge filter system and the pressure drop Δp_{tank} occurring during a regeneration pulse (see Chapter 4.4.1.3).

4.4.1.1 Determination of filter media resistance

The filter medium resistance was determined by measuring the differential pressure across the filter cartridges in the unloaded state. A distinction is made between new and aged filter media (see Chapter 4.2.2).

Filter medium resistance of new media

According to the filter equation 4.11, the filter medium resistance should remain constant at different face velocities. Experimentally, however, a linear relationship between volumetric flow rate and filter medium resistance was observed. This effect is attributed to the cartridge filter system and the pleating of the filter medium within the cartridges. The filter equation 4.8, is only valid for flat filter samples. In pleated cartridges, both laminar and turbulent flow regions occur. Consequently, the pressure drop exhibits a linear and a quadratic dependence on the volumetric flow rate. Furthermore, the measurement position within the cartridge filter system introduces an additional pressure drop caused by flow deflections in the cartridge filter system, which also follows a quadratic dependence on the volumetric flow rate. The measured pressure drop can

therefore be expressed as

$$\Delta p = K_{\text{medium}} \cdot w_f + K_{p,1} \cdot w_f + K_{p+A,2} \cdot w_f^2 \quad (4.15)$$

where K_{medium} is the filter medium resistance, $K_{p,1}$ represents the resistance of the laminar flow regions within the pleated cartridges, and $K_{p+A,2}$ accounts for the resistance of the turbulent flow regions and flow deflections in the cartridge filter system [67]. Thus, the resistance of the filter medium is influenced by pleating as well as by flow deflections in both the cartridge filter system and the filter cartridges, resulting in a dependence on operating conditions. A single filter medium resistance value, is therefore insufficient for a complete description. The measurement of the individual resistance contributions was not feasible within this work. Instead, pressure drop and flow velocity were measured at different operating conditions, and a resistance value was derived that incorporates all contributions and varies with operating conditions. Hereafter, the term filter medium resistance refers to this corresponding resistance.

Filter medium resistance of aged media

To investigate the dust collection system under steady-state conditions, the filter medium was aged. This was achieved by repeated regeneration cycles until no significant difference in the pressure drop of the unloaded, cleaned filter medium was observed under identical operating conditions. In this study, filter medium aging was completed after approximately 800 regeneration cycles. Figure C.4 in the appendix shows the pressure over time. Figure 4.5 shows the aged filter medium resistance as a function of volumetric flow rate. Measurements were conducted at different fan frequencies set at the cartridge filter system, as the resistance depends on the volumetric flow. To ensure comparability, all other operating parameters were kept constant. The filter cartridges were regenerated with a cycle time of 30 s, corresponding to a circulation time of 60 s. The measurements were carried out with a tank pressure of 5 bar, a valve opening time of 0.12 s, and a dust mass flow of 2.8 kg/h. To achieve steady-state conditions, an equilibration time of 1 h was applied after each frequency change. During this equilibration period, the usual offline regeneration was omitted. This approach was necessary because offline regeneration cleans the filter medium more effectively, since particles removed from the medium are less likely to be transported back to the surface and no counterpressure is present. This would otherwise have required a longer equilibration time. For the modeling of the power demand, the filter medium resistance must be determined

under conditions where both filter cartridges are cleaned. For this purpose, particle feeding was stopped shortly before regeneration. Subsequently, the first cartridge was regenerated, followed by the second. The results for the filter medium resistance show that under these conditions, increasing fan frequency does not lead to a higher volumetric flow rate. At higher frequencies, cartridge regeneration becomes less effective because of the increased counterpressure at the filter surface. As a result, more filter area becomes blocked, the resistance increases, and only the local face velocity rises with increasing frequency. The data points shown in Figure 4.5 form the basis for calculating the system's power demand.

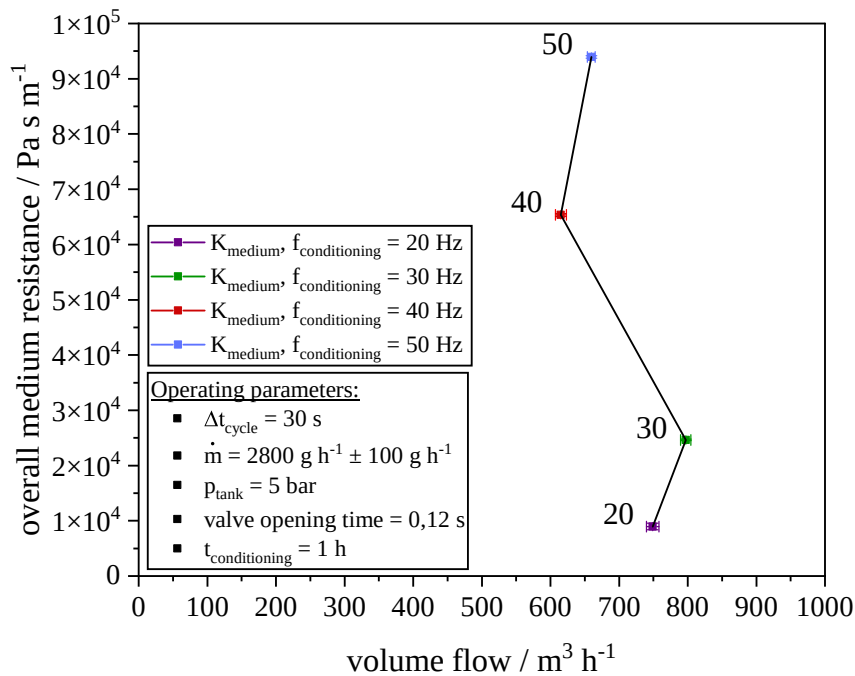


Figure 4.5: Filter medium resistance as a function of the set frequency.

4.4.1.2 Determination of filter cake resistance

The filter cake resistance was determined by measuring the pressure drop between the raw gas and clean gas sides during continuous loading of the filter

cartridges without regeneration. This measurement requires a constant filtration velocity and a constant raw gas concentration. As the filter cake grows with time, the resistance increases, which in turn causes a decrease in volume flow at constant fan power. Therefore, the volume flow was kept constant by adjusting the fan frequency. Combined with a constant particle mass flow, this results in a constant raw gas concentration. Figure 4.6 shows the pressure drop between the raw and clean gas compartments as a function of the dosed particle mass. The three measurement curves differ in the initial fan frequency. For each

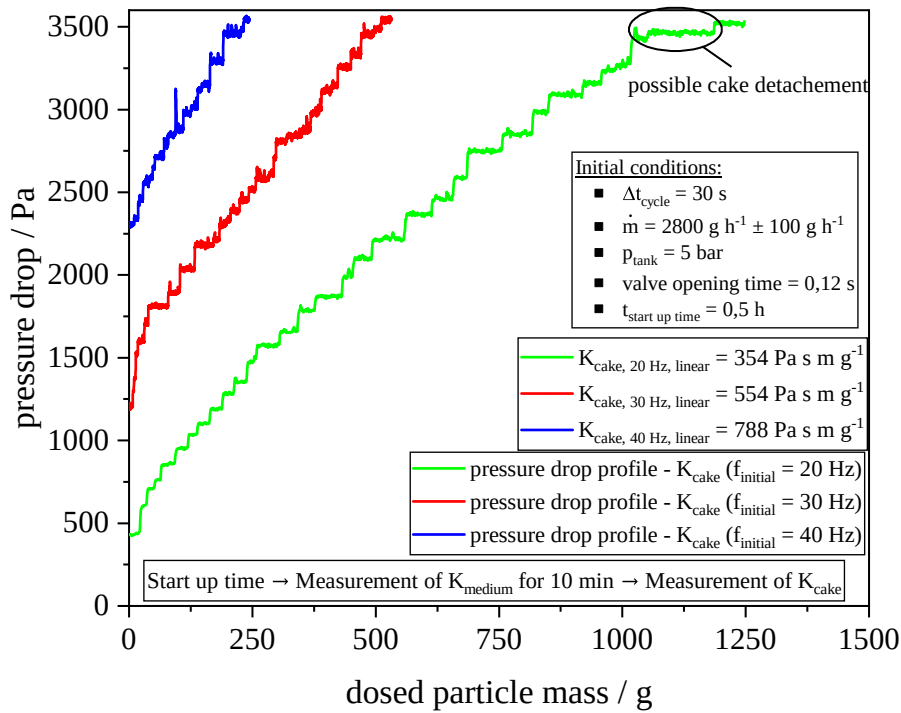


Figure 4.6: Pressure drop across the filter cartridges as a function of the dosed particle mass for different initial frequencies.

experiment, the system was operated in a stationary state with a start up period of 30 minutes. According to the filter equation 4.8, the filter cake resistance is derived from the slope of the pressure drop curve, the dosed particle mass, the filter medium resistance, and the filtration velocity. For this reason, an indirect measurement of the filter medium resistance was performed for 10 minutes after the run-in period, followed by particle dosing. To ensure constant

raw gas concentration and filtration velocity, the fan frequency was manually adjusted. The increase in pressure drop with dosed particle mass differs for the various initial frequencies. This behavior is attributed to different particle deposition in the pleat bottoms of the cartridges. With increasing frequency, blockage of the pleat bottoms becomes more pronounced, reducing the available filter area. Consequently, the same dosed particle mass is deposited on a smaller filter surface, leading to faster cake growth. In addition, the pressure drop rises at the beginning of the experiment. Residual particles remaining on the cartridge surface after regeneration form a cracked deposit structure (see Figure C.5), which quickly becomes clogged during the initial loading phase, causing a rapid increase in pressure drop. Thereafter, the slope flattens. When averaged linearly over the entire measurement period, the lowest filter cake resistance was obtained for the longest experiment. The calculated filter cake resistances for the different initial frequencies are given in the legend of Figure 4.6. Figure 4.7 shows the measured filter cake resistance as a function of fan frequency. The red data points correspond to measurements of the pressure

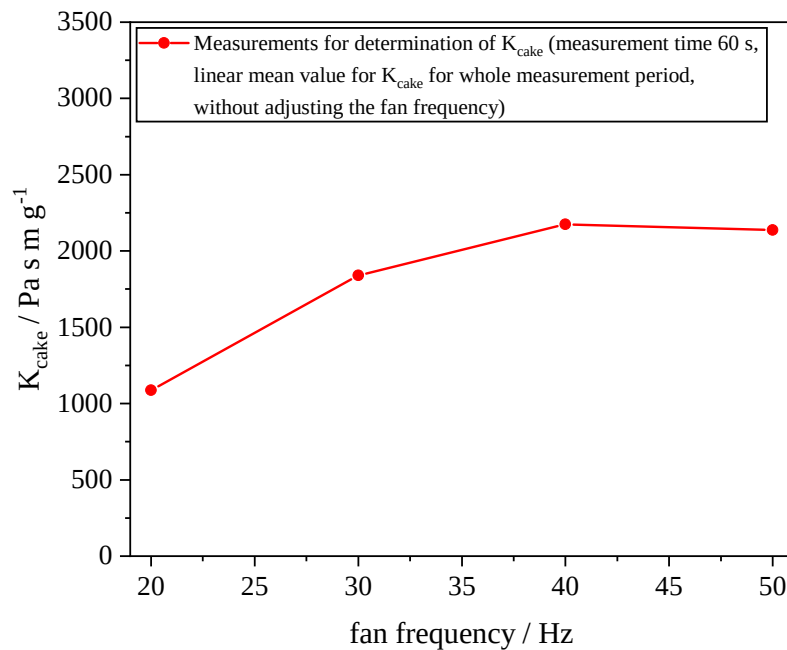


Figure 4.7: Filter cake resistance K_{cake} as a function of the initial fan frequency for different operating states.

drop conducted over only one minute. In this case, both filter cartridges were

online-regenerated at the beginning. As before, an indirect measurement of the filter medium resistance was first carried out for ten minutes, since it is required to calculate the filter cake resistance. The cartridges were then loaded with particles. During this short measurement period, no volume flow adjustment was applied, as a regulation was not feasible. Consequently, the calculation of the filter medium resistance relies on the assumption of a constant volume flow (see Chapter 4.4.1.1). In the model equations, the filter cake resistance is adjusted based on the one-minute measurements. This choice reflects the more realistic correspondence of the measurement duration with the cycle time of the system under real operating conditions. Similar to the filter medium resistance, the filter cake resistance depends on the fan frequency. Therefore, the fan frequency must be specified to calculate the operating point with the model equations. For input frequencies between the four measured values, the filter cake resistance is determined by linear interpolation of the adjacent data points.

4.4.1.3 Determination of the power requirement for filter regeneration

The power demand for filter regeneration is calculated according to Equation 4.7 from the pressure drop in the tank during regeneration Δp_{tank} , the tank volume V_{tank} , and the cycle time Δt_{cycle} . The tank volume of the cartridge filter system

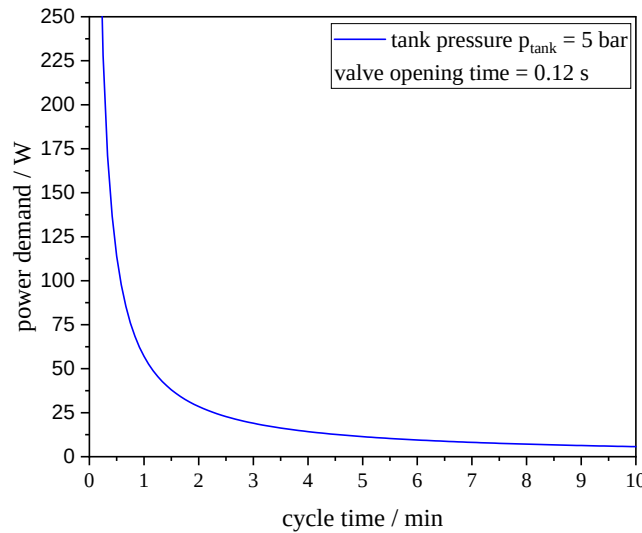


Figure 4.8: Power demand of the pressure pulse as a function of the cycle time.

is 9 L. To determine the tank pressure drop Δp_{tank} , the compressed air tank is filled, the inlet valve is closed, a regeneration is carried out, and the differential pressure in the tank is measured. All experiments in this work were performed at a tank pressure of 5 bar. For 5 bar the pressure decrease in the tank during regeneration is 3.8 bar. At shorter cycle times, the power demand for cartridge filter regeneration increases significantly. Figure 4.8 shows the power demand of the regeneration process as a function of the cycle time.

4.4.2 Emission modeling of jet-pulsed cleaned cartridge filter system

The model equations describe the emissions according to Equation 4.3. Consequently, the model includes only direct particle penetration as the emission mechanism. According to Binnig et al. [56], this mechanism is the primary cause of particle emissions in surface filtration. The parameters E_D , $E_{\min}$ and t_{Reg} in Equation 4.3 must therefore be adjusted to the experimental results. Figure

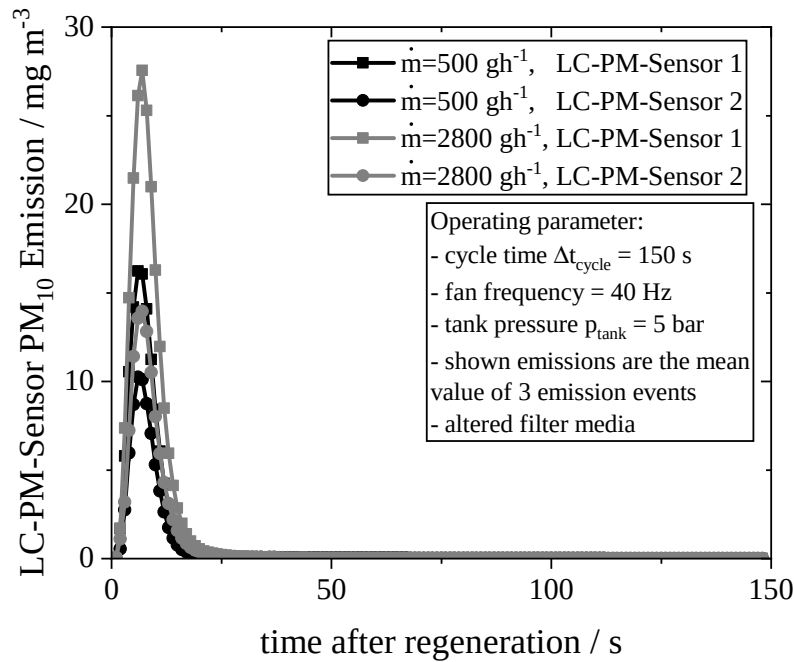


Figure 4.9: Temporal evolution of the outlet particle concentration during filter regeneration at two mass flow rates.

4.9 shows the temporal evolution of the outlet particle concentration following the regeneration pulse for two dust mass flows: $\dot{m} = 500 \text{ g/h}$ and $\dot{m} = 2800 \text{ g/h}$.

Measurements were obtained using two LC-PM-Sensors positioned downstream of the filter. Each curve represents the mean value of three regeneration events. Operating parameters were kept constant with a cycle time of $\Delta t_{\text{cycle}} = 150 \text{ s}$, a fan frequency of 40 Hz, and a tank pressure of $p_{\text{tank}} = 5 \text{ bar}$. The chosen operating condition was used because it represents a realistic system state, reflecting typical process parameters with respect to both the applied fan frequency and the regeneration cycle time. The emissions increase at the beginning of the regeneration pulse, reaching a maximum value $c_{\text{max,out}}$ and subsequently decrease exponentially towards the steady-state concentration c_{min} . The figure reveals several key observations. First, the two LC-PM-Sensors measure different levels of emissions. LC-PM-Sensor 1 consistently records higher emission concentrations compared to LC-PM-Sensor 2. Here, LC-PM-Sensor 1 and 2 are different sensors compared to the investigations at the wet separator. At higher mass flow rates, the measured values of LC-PM-Sensor 1 are approximately a factor of ≈ 1.7 greater, while at lower mass flow rates the difference is about a factor of ≈ 1.4 . This offset may result either from actual differences in particle concentration between the measurement locations or from differences in the response characteristics of the LC-PM-Sensors. Despite this offset, both sensors display an identical decay behavior following the regeneration pulse, indicating consistent dynamic response characteristics. The adaptation of the maximum separation efficiency E_D is performed first. The determination is based on the measurement data shown in Figure 4.9. To calculate the maximum separation efficiency, the mean outlet concentration for each frequency shown is determined once the zero-emission level is reached. The zero-emission level is achieved during the last 25 s of each cycle. By averaging inlet and outlet concentrations at the different frequencies, the mean maximum separation efficiency E_D is determined to be 0.999 942. After determining the maximum separation efficiency E_D , the parameters E_{min} and t_{Reg} are adjusted. The parameter E_{min} represents the minimum separation efficiency during a regeneration pulse. It quantifies the temporary reduction in filtration efficiency caused by the detachment of the dust cake and the direct penetration of particles through the filter medium. The determination of E_{min} is based on experimental emission data obtained during regeneration events and are represented in Figure 4.9. For each experiment, the maximum outlet concentration following the pulse, $c_{\text{out,max}}$, is identified from the measured emission curve. The corresponding inlet concentration, c_{in} , is derived from the ratio of dust mass flow to gas volume flow. The minimum

separation efficiency is then calculated according to

$$E_{\min} = 1 - \frac{c_{\text{out,max}}}{c_{\text{in}}}. \quad (4.16)$$

Due to the different sensor behavior at the emission peak, the following value is obtained for LC-PM-Sensor 1: $E_{\min, \text{LC-PM-Sensor1}} = 0.98787$ and the following value for LC-PM-Sensor 2: $E_{\min, \text{LC-PM-Sensor2}} = 0.99245$. These values are averaged in the subsequent analysis to $E_{\min} = 0.99016$. However, $E_{\min}$ has a significant influence on the calculation of the resulting emission, particularly at increasing mass flow rates. The regeneration time constant t_{reg} was determined from the temporal evolution of the emission signal following each regeneration pulse (see Figure 4.9 for temporal emission decay). The regeneration process was assumed to follow a first-order exponential recovery of the separation efficiency according to Equation 4.3. To determine the regeneration time constant t_{reg} , the exponential decrease of the emission signal after a regeneration pulse was linearized by applying the natural logarithm. The original concentration curve $c_{\text{out}}(t)$ decreases exponentially over time. By subtracting the final concentration $c_{\min}(t)$ from the measured signal, the remaining part of the curve represents the pure exponential decay. When the natural logarithm is applied to these adjusted concentration values, the curved exponential relationship becomes a straight line. The slope of this line indicates how quickly the emission decreases during the recovery phase. Since the slope of the logarithmic curve is the reciprocal of the time constant, the regeneration time t_{reg} can be obtained as the inverse of the absolute value of the slope. In this way, the logarithmic transformation enables direct quantification of the exponential recovery behavior from the experimental data. The resulting mean t_{reg} from the measurements shown in Figure 4.9 is 17.47 s.

4.5 Comparison of Parametrized Model Predictions with Experiments

This chapter presents the results of the parametrized model equations with respect to the power demand (see Chapter 4.4.1) and the separation efficiency (see Chapter 4.4.2) of the cartridge filter system, and compares these results with experimental measurements. The measurements in Chapter 4.4.1.1 showed that increasing the fan frequency causes only small changes in the volumetric flow rate. As a result, different cycle times cannot be realized under comparable

operating conditions. This limits the experimentally accessible operating range. Figure 4.10 illustrates the relationship between the required power for operating the cartridge filter system as a function of the emitted dust mass concentration for various operating conditions. Four model based and calculated curves are shown, each corresponding to a distinct combination of dust mass flow rate, volumetric flow rate, and fan frequency. The curves represent model predictions for operating points at $\dot{m} \approx 500$ g/h and $\dot{m} \approx 2800$ g/h at 20 Hz and 40 Hz. Each point on the model curves represents a specific cycle time (10, 15, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120, 130, 140, 150, 160, 170, 180, 240, 300, 360, 420, 480, 540, 600s). Experimental data points corresponding to a cycle time of $\Delta t_{\text{cycle}} = 150$ s are plotted alongside the model curves. Each experimental data point represents the mean value obtained of three representative emission events. The emitted dust mass concentration was measured using LC-PM-Sensors. The power required to operate the cartridge filter system was calculated according to Equations 4.5 - 4.7 and is primarily determined by the pressure drop across the filter cartridges, the volumetric flow rate, and the cycle time. The reported power demand values represent the minimum power demand for operating the cartridge filter system, as the calculation does not account for the efficiency of the fan or the compressed air supply. All measurements were performed at a tank pressure of 5 bar and a valve opening time of 0.12 s. The model equations reproduce the experimental results with varying accuracy depending on the operating parameters. For the power demand, the model equations reproduce the corresponding experimental values with good accuracy (≤ 20 %) across all measurements. For a mass flow of $\dot{m} \approx 500$ g/h, the deviations between the calculated and measured emissions range from 68 % (20 Hz) to 4 % (40 Hz). However, for the higher mass flow rate ($\dot{m} \approx 2800$ g/h) the emission values differ between model and experiment at both frequencies. At 20 Hz, the deviation is approximately 300 %, and at 40 Hz it increases to roughly 800 %. These large deviations can be partly explained by the previously discussed sensitivity of the minimum separation efficiency E_{min} (see Chapter 4.4.2). At higher mass flow rates, the influence of E_{min} on the outlet concentration becomes more pronounced. Also, the model equations include only the mechanism of direct particle penetration, which is negligible at 20 Hz and likely still small at 40 Hz. The emission measurement response of the LC-PM-Sensor is consistent with reported findings in the literature, which indicate that LC-PM-Sensors are able to reproduce local trends and capture emission peaks, with varying accuracy regarding the peak magnitude. [29] [32] Overall, the calculated power demand from the model equations agrees with the experimental results (≤ 20 %), whereas larger deviations occur for the

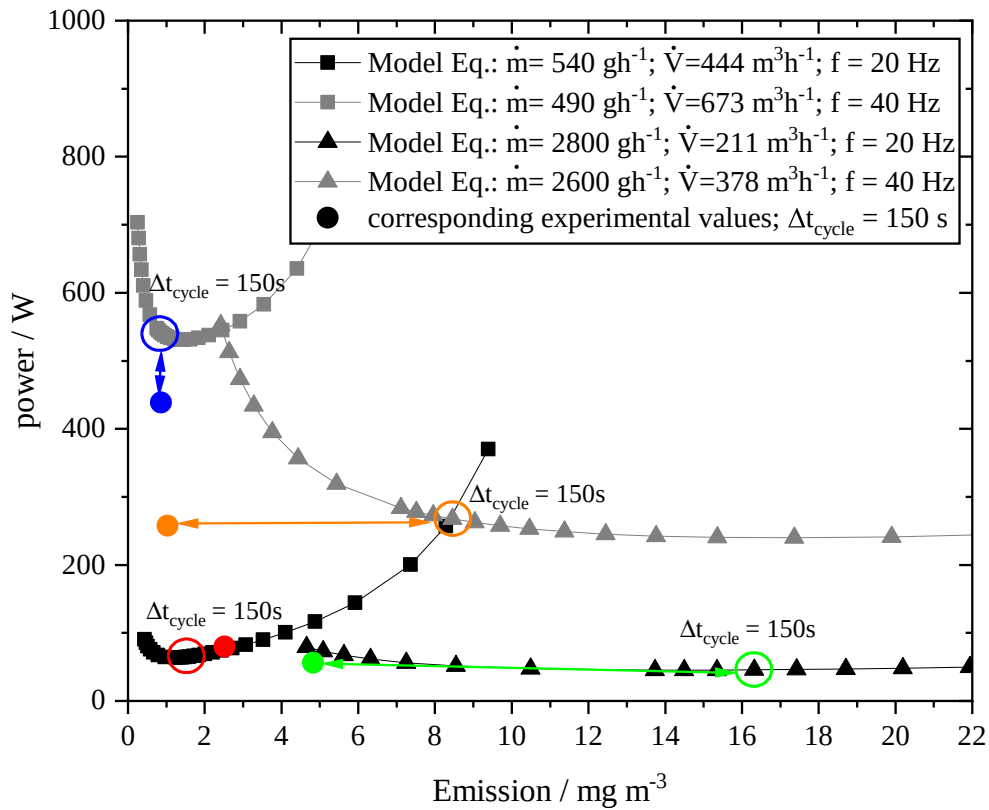


Figure 4.10: Required power of the cartridge filter system as a function of emitted dust mass concentration for different operating conditions. Model points correspond to individual cycle times; experimental points represent 1 h averages measured with the LC-PM-Sensors. All measurements were conducted at 5 bar tank pressure and 0.12 s valve opening time.

emissions (up to 800%).

4.6 Conclusion

This chapter investigated the suitability of LC-PM-Sensors for monitoring and model-based assessment of industrial dust collection systems. The results demonstrate that LC-PM-Sensors, despite their limited specification range, are capable of providing emission measurements to identify characteristic filtration behavior and to support model based predictions.

The deviations between modeled and experimentally measured operating points

remained below 20 % for the predicted power demand across all investigated operating conditions. This indicates that the model equations for pressure loss and regeneration energy represent the relevant physical dependencies for practical application. In contrast, the deviations between modeled and measured emissions varied. For low inlet dust mass flow rates (≈ 500 g/h), the discrepancies remained moderate ($\leq 70\%$). However, at higher mass flow rates (≈ 2800 g/h), the deviations between the predicted and measured emission levels increased substantially ($\leq 800\%$). This behavior can be attributed to the sensitivity of the minimum separation efficiency $E_{\min}$ and the simplifying assumptions within the model, which currently considers only direct particle penetration as an emission mechanism.

The LC-PM-Sensor measurements aligned with established findings in the literature [29, 32], confirming their capability to reproduce qualitative emission patterns and to detect peak structures within filtration cycles. Although quantitative deviations remain, the sensor data captured temporal trends and changes in operating conditions, enabling comparison with the model equations and assessment of operating states.

Overall, this chapter showed that LC-PM-Sensors are suitable for monitoring emission behavior in industrial dust collection systems and can serve as a practical data source for adjusting and validating empirical model equations. Further work is required to improve the quantitative prediction of emissions at higher dust loadings and to refine the underlying separation models. A modification of Equation 4.3 by implementing a mass-flow-dependent $E_{\min}$ is proposed, as this approach may contribute to reducing the pronounced deviations at elevated mass-flows. The demonstrated agreement for power demand and the reproducibility of emission trends underline the potential of LC-PM sensors as an accessible and cost-effective tool for process monitoring and for supporting the development of model-based monitoring approaches for dedusting systems.

5

Conclusion and Outlook

This study investigated the applicability of LC-PM-Sensors for particle measurements in gas cleaning systems, with a particular focus on particle number concentration and particle size distribution under controlled laboratory conditions and during operation of a wet separator. In addition, the study examined the use of LC-PM-Sensors in a pulse-jet-cleaned cartridge filter system to compare measured data with literature-based model equations and to assess whether operating states can be determined from the measured emission data. Section 5.1 presents the measurements conducted under idealized laboratory conditions. Section 5.2 reports the results obtained when the LC-PM-Sensors were installed in the wet separator. Section 5.3 summarizes the findings from the implementation of LC-PM-Sensors in the cartridge filter system.

5.1 Low-Cost PM-Sensors for Emission Characterization

This study examined the use of LC-PM-Sensors for particle number concentration and particle size distribution measurements under controlled conditions relevant to wet separation systems. Five LC-PM-Sensors were tested in parallel with a RI at relative humidity levels of 55 % and 95 %.

Across both humidity conditions, the deviation between LC-PM-Sensors and RI measurements followed the same concentration-dependent pattern. No effect of relative humidity on this deviation was identified for the used particle

system. Up to particle number concentrations of approximately $6 \times 10^4 \text{ 1/cm}^3$, the LC-PM-Sensor - RI deviation was represented by a third-order polynomial correction function with sensor-specific coefficients.

Comparison of the five LC-PM-Sensors showed only small differences within the sensor array. The mean relative standard deviation changed from 5.75 % at 55 % relative humidity to 5.95 % at 95 %, and the mean absolute relative deviation from 4.25 % to 4.46 %. LC-PM-Sensor 1 differed consistently from the other sensors, possibly due to its different production date.

In addition to total particle number concentration, the LC-PM-Sensors also reproduced the RI measured PSDs and their temporal development at both humidity levels. The strongest PSD shifts occurred at high relative humidity in the size range from approximately $0.3 \mu\text{m}$ to $0.7 \mu\text{m}$. The observed PSD shift indicates a change in distribution shape rather than uniform particle growth and suggests changes in particle agglomeration. The LC-PM-Sensors also reproduced the trends in the $\Delta\text{PC}_{\text{N,PM}_{0.5}}$, $\Delta\text{PC}_{\text{N,PM}_{1.0}}$, and $\Delta\text{PC}_{\text{N,PM}_{2.5}}$ fractions.

On this basis, the correction factor α_1 was developed for total particle number concentration and the correction factors $\alpha_{2,i}$ for the individual PSD size classes. Since both showed sensor-specific variation, they were determined separately for each sensor. Together, these factors enabled correction of total particle number concentration and PSD.

The results show that the investigated LC-PM-Sensors can be used for particle number concentration and PSD measurements under the investigated controlled conditions when sensor-specific correction is applied.

5.2 Application of Low-Cost PM-Sensors for Emission Characterization of a Wet-Separator

The objective was to assess the performance of LC-PM-Sensors at different measurement positions in the wet separation test facility under operating conditions and to examine whether correction approaches based on laboratory measurements can be applied to particle number concentration and particle size distribution measurements under these conditions. Following the laboratory measurements, the LC-PM-Sensors were installed at two positions in the wet separator. At the raw-gas channel, the installed LC-PM-Sensor 2 underestimated the particle number concentration, measuring approximately $6.4 \times 10^4 \text{ 1/cm}^3$ compared with $8.9 \times 10^4 \text{ 1/cm}^3$ measured by the RI. Both concentrations exceeded the range used to derive the third-order polynomial correction function,

and extrapolation beyond its upper limit of approximately $4 \times 10^4 \text{ 1/cm}^3$ caused overestimation after correction. At the second measurement position above the droplet separator within the wet separator, four LC-PM-Sensors (1, 3, 4 and 5) measured particle number concentrations within the validity range of the correction function. Their deviations from the RI ranged from 34–48% and decreased to 1–20% after application of the polynomial correction. LC-PM-Sensor 5 showed the smallest deviation at 1% and reproduced both mean values and dynamic trends. The remaining deviations were attributed to sensor-specific constant scaling errors and could be compensated by individual scaling factors. The extended evaluation in the wet separator further showed that the LC-PM-Sensors tracked local particle concentration trends across all examined particle size classes, including operation beyond their nominal limits. Before application of the scaling factors α_1 and $\alpha_{2,i}$, most sensors reproduced the $\Delta PC_{N,PM_{0.5}}$ fraction, whereas LC-PM-Sensor 3 underestimated it. Compared with the measurement chamber, a higher proportion of submicron particles was observed in the wet separator, likely due to the enhanced removal of larger particles, resulting in $\Delta PC_{N,PM_{0.5}}$ concentrations exceeding the specified maximum of 3000 1/cm^3 by one order of magnitude. The $\Delta PC_{N,PM_{1.0}}$ fraction was generally underestimated, whereas $\Delta PC_{N,PM_{2.5}}$ was overestimated by LC-PM-Sensors 3 and 5. After application of the scaling factors, all sensors overestimated the $\Delta PC_{N,PM_{0.5}}$ fraction but agreed more closely with the RI for $\Delta PC_{N,PM_{1.0}}$. For $\Delta PC_{N,PM_{2.5}}$, all LC-PM-Sensors shifted toward lower values, which improved agreement with the RI. These results were consistent with the previous findings, according to which the LC-PM-Sensors performed best in the $0.3 \mu\text{m}$ to $0.5 \mu\text{m}$ size range. After application of the scaling factors, however, the accuracy in this class decreased, except for LC-PM-Sensor 3. This indicates that the effect of the corrections depended on both the particle size distribution and sensor-specific characteristics.

5.3 Application of Low-Cost PM-Sensors for Emission Characterization of a Cartridge Filter System

This chapter examined the use of LC-PM-Sensors for monitoring and model-based evaluation of a jet-pulse cartridge filter system, with the aim of extracting operational information from measured emission data. The analysis examined whether LC-PM-Sensors provide the temporal and quantitative resolution required to monitor and evaluate the operating state of modular extraction units.

The sensors were not calibrated, in order to assess their applicability in the investigated system without prior adjustment. The assessment was based on model equations derived from empirical correlations in the literature, which offered a preliminary description of emission behavior and power demand as functions of the operating parameters. These equations served as a framework for predicting operating states and for identifying energy- and emission-optimized conditions. LC-PM-Sensor measurements were subsequently used to adjust and validate the emission-related components of these model equations by comparing measured emission profiles with corresponding model predictions. Overall, the results showed that LC-PM-Sensors can be used to detect emission trends of the investigated filter system and to compare the measured data with the corresponding model predictions. Despite their limited specification range, the sensors provided emission measurements with sufficient temporal resolution to identify characteristic filtration behavior and to support model-based predictions. The parametrized model equations for power demand and emission behavior were compared with measurements of the filter system, while LC-PM-Sensor data were used for the emission measurements. The comparison between modeled and experimentally measured operating points showed good agreement for the predicted power demand across all investigated operating conditions, with deviations remaining below 20 %. This indicated that the model equations for pressure loss and regeneration energy captured the measured dependencies of the system. The deviations between modeled and measured emissions were up to 70% at an inlet dust mass flow rate of approximately 500 g/h and up to 800% at approximately 2800 g/h. The deviations resulted from the influence of $E_{\min}$ on the calculated emissions and from the model assumption that emissions occur only by direct particle penetration. The LC-PM-Sensor measurements reproduced qualitative emission patterns and characteristic peak structures within the filtration cycles. The sensor data captured temporal trends and changes in operating conditions and were used to compare the measurements with the model equations and to assess operating states. In conclusion, this investigation showed that LC-PM-Sensors represent a practical and accessible tool for monitoring emission behavior in industrial dust collection systems and for supporting the validation and improvement of empirical model equations.

5.4 Outlook

The results of this work show that LC-PM-Sensors can be used in dedusting systems beyond their specified limits, extending their usable range by at least one order of magnitude.

In addition to concentration measurement, further research should investigate the capability of LC-PM-Sensors to resolve particle size distributions for different dust types. It remains unclear whether the measurement of concentrations far beyond the nominal specification depends on particle size or on dust properties such as refractive index and mean particle diameter. Such investigations are particularly relevant given that the Most Penetrating Particle Size (MPPS, $\approx 0.3 \mu\text{m}$ to $0.5 \mu\text{m}$) lies precisely within the size range in which the LC-PM-Sensors showed the smallest deviations after pre-processing. Their deployment in this context may also enable condition monitoring of filter elements, support predictive maintenance strategies, and facilitate more reliable determination of filter ageing or performance degradation.

The emission model requires further modification. In particular, a mass-flow-dependent E_{min} is expected to reduce the deviations observed at higher dust loadings. Moreover, the sensor-specific behaviour of LC-PM-Sensors across different test dusts should be characterised to allow the development of generalised, transferable correction schemes. Finally, integrating LC-PM-Sensor data automatically into digital twins of dedusting systems offers significant potential for advancing digitalisation in gas-particle separation. Such integration would support real-time model updating, enhance predictive accuracy, and enable adaptive process control. These research directions indicate further fields of application for LC-PM-Sensors in measurement and monitoring tasks in dedusting systems.

List of Publications

Peer-Reviewed Publications

- [32] **Reinke, F.**, Meyer, J., and Dittler, A. “Investigation of the potential of in-line particle concentration measurements in gas particle separation processes by using low-cost particulate matter sensors.” en. In: *Journal of Aerosol Science* 183 (2025), p. 106476. DOI: [10.1016/j.jaerosci.2024.106476](https://doi.org/10.1016/j.jaerosci.2024.106476). (Visited on 02/11/2025).
- [68] **Reinke, F.**, Hafen, N., Haussmann, M., Novosel, M., Krause, M. J., and Dittler, A. “Applied Geometry Optimization of an Innovative 3D-Printed Wet-Scrubber Nozzle with a Lattice Boltzmann Method.” In: *Chemie Ingenieur Technik* 94.3 (2022), pp. 348–355. DOI: <https://doi.org/10.1002/cite.202100151>.
- [69] **Reinke, F.**, Straube, C., Meyer, J., and Dittler, A. “Additive Manufacturing in Gas Cleaning Applications.” In: *Industrializing Additive Manufacturing*. Cham, 2024, pp. 389–406. DOI: https://doi.org/10.1007/978-3-031-42983-5_26.

Other Publications

- [70] Reinke, F., Meyer, J., Dittler, A., and Novosel, N. “P1.1 - Entwicklung eines Low-Cost PM Sensorenclusters zur Untersuchung des Abscheideverhaltens eines Nassabscheiders.” In: *Poster*. 15. Dresdner Sensor-Symposium 2021. Online, 2021, pp. 115–119. DOI: [10.5162/15dss2021/P1.1](https://doi.org/10.5162/15dss2021/P1.1). (Visited on 11/21/2025).

Conference Talks

- [71] **Reinke, F.**, Meyer, J., and Dittler, A. “Real-world application of low-cost PM sensors in dedusting systems.” In: FILTECH 2023, The Filtration Event. Cologne, 2023.
- [72] **Reinke, F.**, Straube, C., Meyer, J., and Dittler, A. “Additive manufacturing in gas cleaning applications.” In: AMPA 2023 Additive Manufacturing for Products and Applications. Lucern, 2023.
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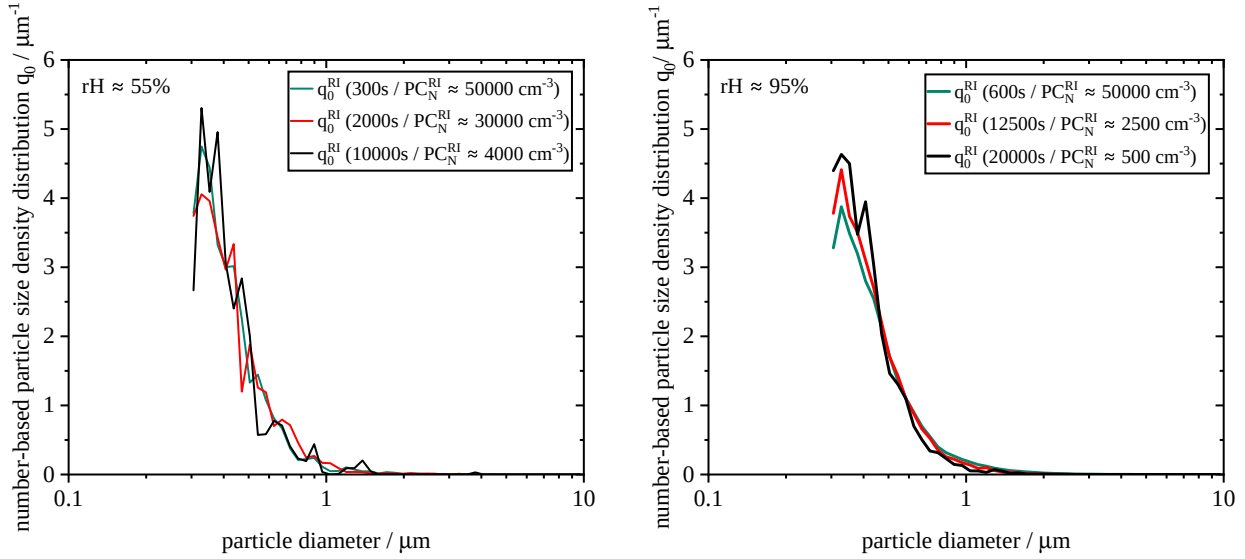


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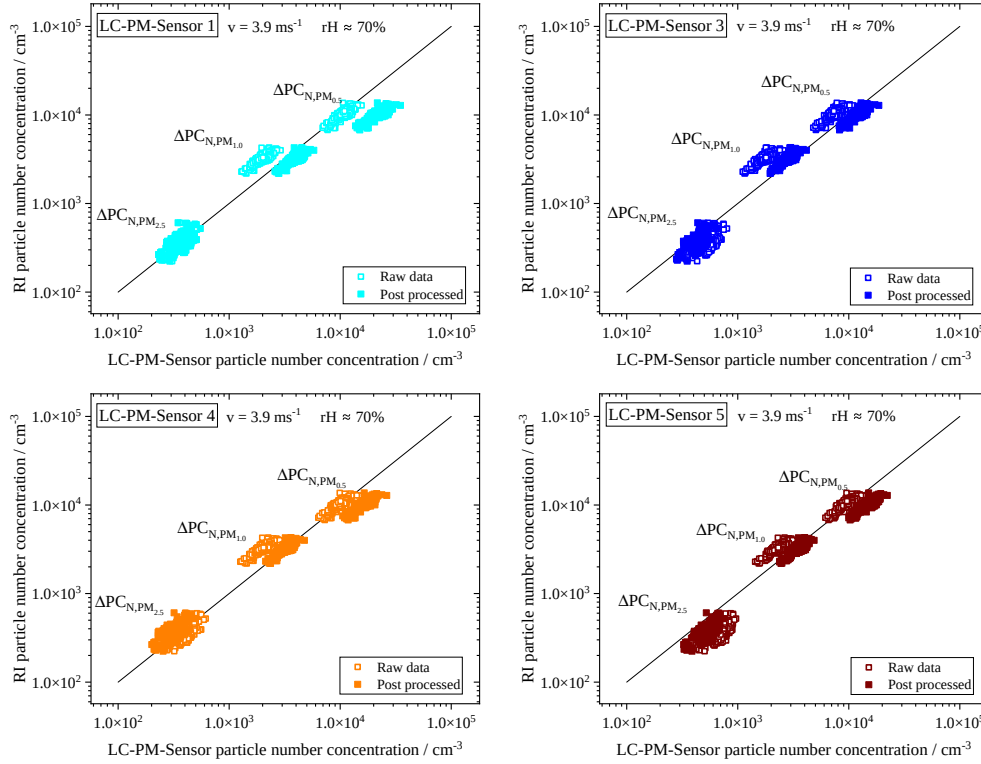


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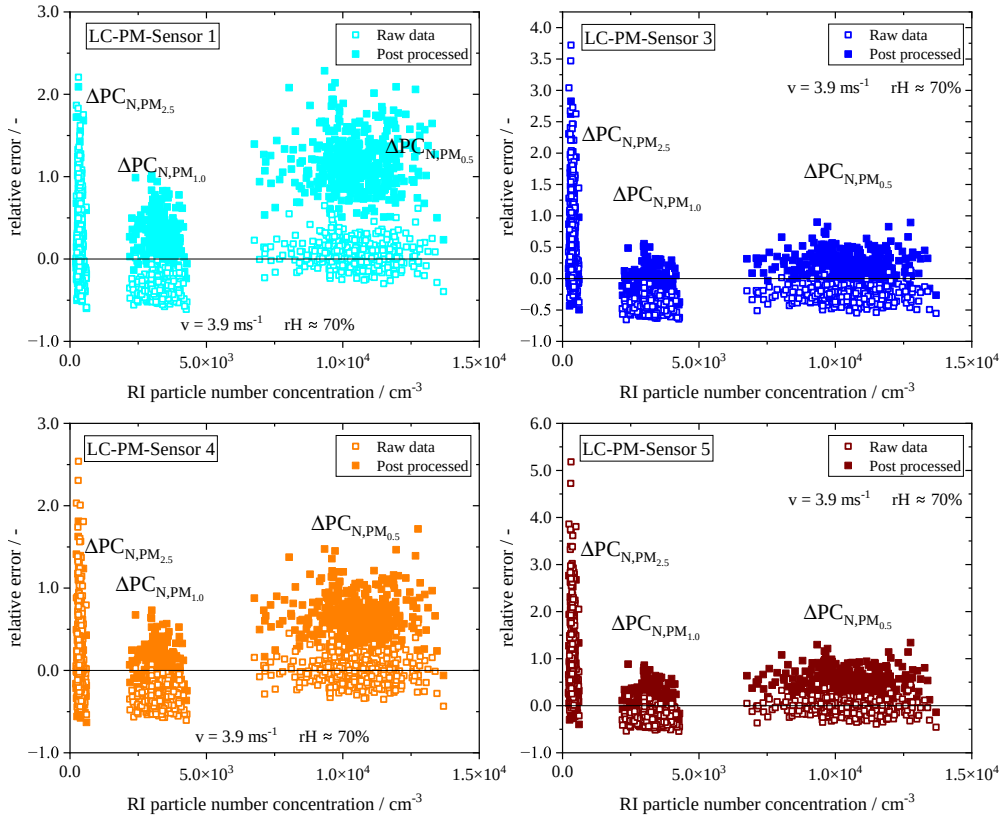


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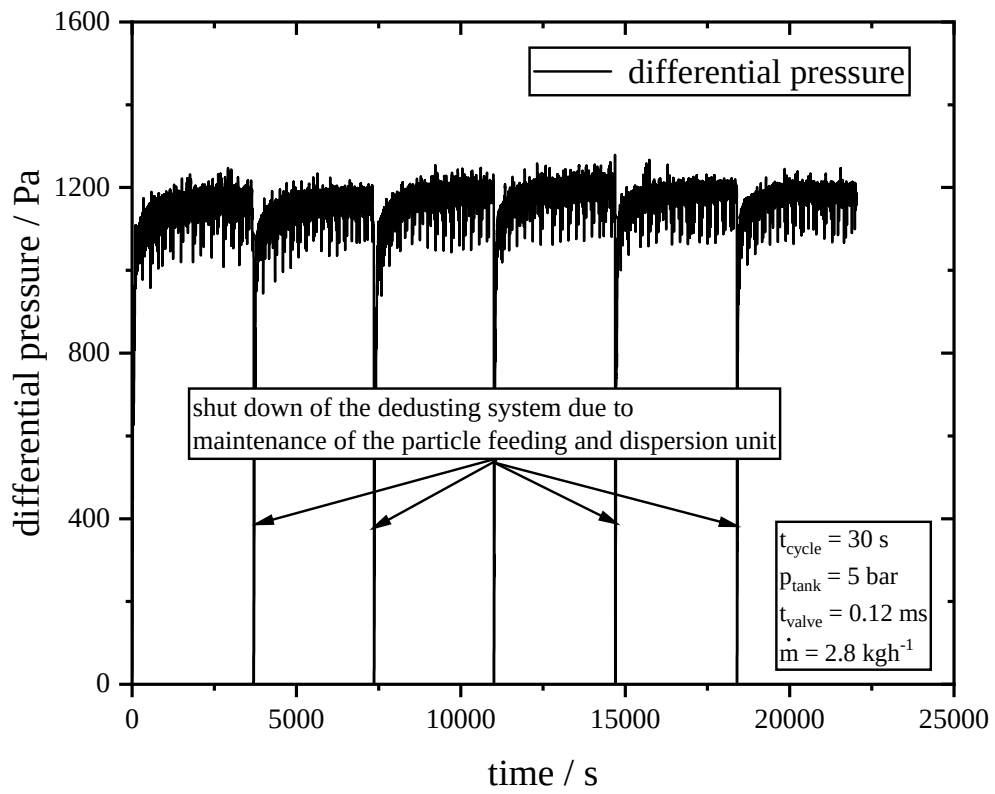


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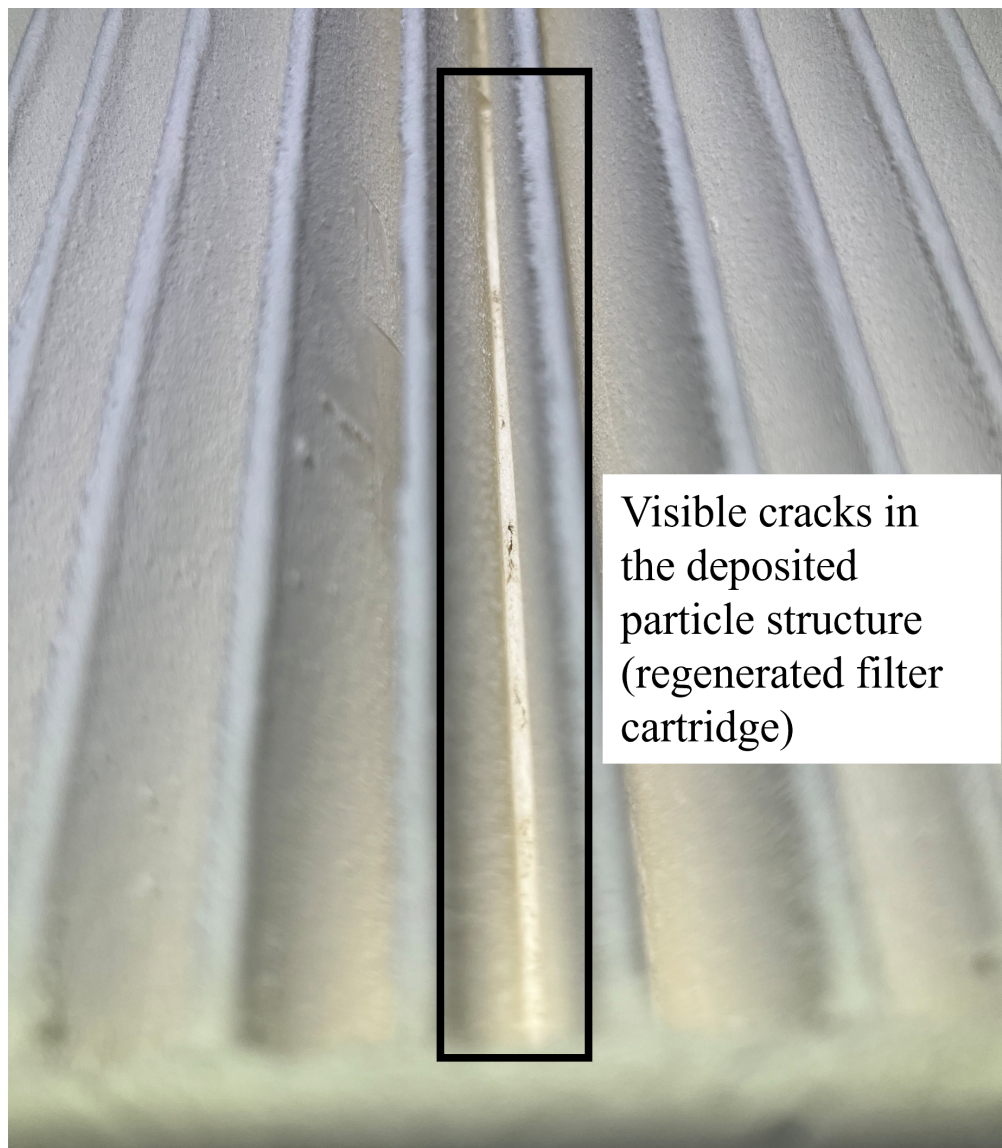


Figure C.5: *Photograph of a cleaned filter cartridge showing visible cracks in the deposited particle structure.*

D List of Abbreviations and Symbols

Abbreviations

Dustomat	Dustomat Dry 3500
Eq.	Equation
EU	European Union
LC-PM-Sensor	Low-cost particulate-matter sensor
MA	Moving average
MARD	Mean absolute relative deviation
PC	Particle concentration
PM _{2.5}	Respirable particulate matter concentration penetrating deeper into the lungs
PM ₁₀	Particulate matter concentration penetrating the upper respiratory system
PM _x	Particulate matter concentration with a median aerodynamic diameter of $x \mu\text{m}$
PNC	Particle number concentration
PSD	Particle size distribution
RI	Reference instrument
rH	Relative humidity
RSD	Relative standard deviation
USB	Universal Serial Bus

Symbols

A_i	Filtration surface
α	Scattering parameter
α_1	Total particle number concentration scale

$\alpha_{2,i}$	Fraction particle number concentration scale
c	Speed of light in vacuum
C_m	Mass-based concentration
$c_{in}(t)$	Inlet particle concentration
$c_{out}(t)$	Outlet particle concentration
$c_{out,max}$	Maximum outlet particle concentration
c_{rawgas}	Raw gas concentration
Δp	Pressure drop
Δp_{tank}	Tank pressure difference
Δt_{cycle}	Cycle time between two regeneration events
$\Delta t_{optimum}$	Optimal cycle time
d_F	Droplet diameter
d_p	Particle diameter
d_S	Cut-off diameter
E	Energy demand per 1000 cm ³
$E(t)$	Time-dependent separation efficiency
E_D	Maximum separation efficiency
E_{min}	Separation efficiency during regeneration pulse
ε	Porosity
f	Frequency
$f_{initial}$	Initial frequency
$h(d_p)$	Adhesion probability
I	Intensity of the light scattered by a single particle
I_0	Intensity of the incident light on the particle
I^*	Relative scattered light intensity
K_i	Time-dependent resistance constant

K_{cake}	Filter cake resistance
K_{medium}	Specific medium resistance
K_{tot}	Overall resistance constant
$K_{p,1}$	Resistance of the laminar flow regions within the pleated cartridges
$K_{p+A,2}$	Resistance of the turbulent flow regions and flow deflections in the Dustomat
λ	Wavelength of the incident light
μ_W	Liquid-to-gas ratio
$\dot{m}$	Mass flow
N	Number-based index
n	Refractive index
P_{fan}	Power demand of the fan
P_{overall}	Total power demand
$P_{\text{regeneration}}$	Power required for compressed air supply during regeneration
Φ	Polarization angle of the scattered wave
$\bar{p}_{\text{filter}}$	Average pressure drop across the filter cartridges
q_0	Differential number-based distribution
Q_0	Cumulative distribution (number-based)
ρ_p	Density of the particle
t	Time after regeneration pulse
$t_{\text{conditioning}}$	Conditioning time for experiments
t_{reg}	Characteristic time after decay to $1/e$ of the initial value
t_{valve}	Valve opening time
u	Inflow velocity
v	Velocity

v_p	Speed of light in the particle
$\dot{V}$	Volume flow
V_{tank}	Volume of the pressure tank
$\varphi(d_p)$	Separation efficiency
W_i	Deposited dust mass
w_f	Filtration velocity
x	Particle number concentration in polynomial correction functions
$x_{50,3}$	Mass/volume median diameter
$\eta(d_p)$	Collision efficiency
θ	Detection angle of scattered light

