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Research Article

An Optical Technology–Based Approach for Emission Opacity Monitoring Derived from the Ringelmann Chart

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Abstract

Smoke opacity monitoring is a key element in the regulatory control of atmospheric emissions from industrial stacks and other combustion sources. Conventional evaluation using the Ringelmann Chart depends on human visual observation and making them susceptible to subjectivity, observer variability, and sensitivity to lighting and background conditions. This paper proposes an optical technology–based framework that quantitatively reproduces and extends the traditional Ringelmann approach through automated and objective measurement. The proposed system integrates photometric sensors or digital cameras with image processing and machine learning algorithms to derive Ringelmann equivalent opacity values in near real time. The framework is conceptually aligned with standardized digital imaging methods, particularly the Digital Camera Opacity Technique (DCOT) defined in ASTM D7520, while maintaining compatibility with legacy Ringelmann based regulatory practices. System architecture, calibration strategy, and representative laboratory and industrial application scenarios are discussed. Recent studies demonstrate strong agreement between optical imaging–based opacity estimation and reference measurements, with coefficients of determination (R^2) typically in the range of 0.92–0.96, alongside improved robustness under varying illumination and background conditions. The proposed approach enables cost effective, verifiable, and integrable smoke opacity monitoring, providing a practical bridge between visual assessment and modern digital emission monitoring systems

Keywords: *smoke opacity, Ringlemann Chart, optical sensors, image processing, deep learning, ASTM D7520, emission monitoring.*

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1. Introduction

Particulate emissions from combustion processes generate smoke containing suspended aerosol particles that can adversely affect ambient air quality and human health. Consequently, smoke opacity remains an important regulatory indicator in industrial and vehicular emission standards. Historically, opacity has been assessed using the Ringlemann Chart, a visual grading method introduced in the late nineteenth century that represents smoke density using five discrete grayscale levels (0–5), approximately corresponding to 0–100% opacity (Ringelmann, 1897; EPA, 2013).

Despite its long-standing use, visual opacity assessment exhibits several inherent limitations. The method is subjective, as perceived smoke darkness varies among observers and depends on training and visual acuity. In addition, observations are strongly influenced by ambient lighting, meteorological conditions, and background characteristics, such as sky brightness or surrounding structures. Visual assessments are typically intermittent rather than continuous, and the results are difficult to archive, verify, or integrate into automated monitoring and control systems (EPA, 2013; ASTM, 2016).

Driven by advances in optical sensors, photometry, digital imaging, and image processing, there has been increasing interest in replacing or augmenting visual methods with instrument-based opacity measurements. Optical techniques enable opacity estimation that is objective, calibrated, and suitable for continuous or semi continuous operation, and that can be integrated into modern industrial monitoring frameworks such as continuous emission monitoring systems (CEMS) and supervisory control platforms (Beutner, 1974; Yuen, 2017).

This transition is reflected in the standardization of camera-based opacity measurement methods, particularly the Digital Camera Opacity Technique (DCOT) formalized in ASTM D7520. DCOT provides a quantitative procedure for deriving plume opacity from image contrast, with defined requirements for camera calibration, background selection, and data processing, and has been accepted in regulatory contexts as an alternative to traditional visual observation under specified conditions (ASTM, 2016; EPA, 2011).

More recently, developments in computer vision and machine learning have further improved the robustness of image-based opacity estimation. Automated plume detection, region of interest selection, and smoke segmentation algorithms reduce reliance on human operators and improve reproducibility under complex background and lighting conditions (Yuen et al., 2018; Pedrayes et al., 2023). These advances enable imaging systems to function not only as documentation tools, but also as quantitative, automated instruments for real time or near real time opacity assessment.

In this context, the present study aims to: (1) develop an optical–computational methodology for automatically producing Ringlemann equivalent opacity values;; (2) review recent literature (2013–2023) on optical and image based smoke monitoring techniques;; (3) discuss potential qualitative testing approaches and industrial applications; and (4) identify key implementation challenges and directions for future research. By maintaining compatibility with the Ringlemann scale while introducing quantitative analysis, the proposed framework seeks to bridge traditional visible emission assessment with contemporary digital monitoring technologies

2. Methodology

2.1 Principles of Optical Measurement and Theoretical Modeling

Optical-based smoke-opacity monitoring generally relies on the fundamental interaction between light and particulate matter suspended in a gaseous medium. When a beam of light propagates through a smoke plume, its intensity is attenuated as a result of absorption and scattering processes caused by aerosol particles. The degree of attenuation provides indirect but quantifiable information about the concentration, size distribution, and optical properties of the particles, and is therefore closely related to plume opacity.

A classical theoretical framework frequently adopted in optical opacity measurement is the Beer–Lambert law, which describes the exponential decay of light intensity as it traverses an absorbing and scattering medium. In its simplest form, the transmitted light intensity I can be expressed as

$$I = I_0 e^{-\beta L}$$

where I_0 is the incident light intensity in the absence of smoke, β is the effective optical attenuation coefficient (encompassing both absorption and scattering effects), and L is the optical path length. Based on this relationship, the fractional opacity O can be defined as: This formulation provides a convenient theoretical basis for transmissometer-based opacity monitors and has been widely applied in industrial emission measurement systems.

However, direct application of the Beer–Lambert law to real smoke plumes is often insufficient, particularly under practical industrial conditions. Combustion-generated smoke is a complex, heterogeneous medium composed of particles with varying sizes, shapes, refractive indices, and chemical compositions. As a result, light attenuation is influenced not only by absorption, but also by multiple scattering phenomena, including forward scattering, backscattering, and lateral diffusion. Additional factors such as turbulence, inhomogeneous particle distribution, gas temperature gradients, and temporal fluctuations in plume density can further violate the assumptions of uniformity and single scattering inherent in the classical Beer–Lambert model.

To address these limitations, industrial optical monitoring systems often incorporate design and modeling adaptations. For example, on-stack transmissometers commonly employ optimized optical geometries, collimated light sources, and spatial filtering techniques to minimize the influence of stray light and multiple scattering. Some systems use dual-wavelength or multi-angle approaches to improve discrimination between absorption and scattering effects, thereby enhancing measurement robustness under variable plume conditions.

In the context of camera-based optical techniques, such as the Digital Camera Opacity Technique (DCOT), the theoretical emphasis shifts from absolute light transmission to image contrast and relative luminance differences between the smoke plume and a reference background. In this case, opacity is inferred from normalized grayscale or luminance values extracted from digital images, rather than from direct intensity readings along a fixed optical path. While this approach departs from the strict Beer–Lambert formulation, it remains conceptually aligned with radiative transfer theory, as plume opacity is still derived from the attenuation of background light by particulate matter.

Consequently, modern optical opacity measurement frameworks can be viewed as hybrid models, combining simplified physical principles with empirical calibration and computational correction. By coupling optical measurements with image processing and statistical or machine learning–based mapping, it becomes possible to account for non-ideal behaviours and to produce stable, reproducible opacity estimates under realistic field conditions. This hybridization is particularly important when translating continuous optical measurements into Ringelmann-equivalent opacity values, which are historically rooted in human visual perception rather than strict photometric quantities.

Then the factional opacity (0) can be defined as:

$$0 = 1 - \frac{I}{I_0}$$

In practical industrial conditions, optical measurements are affected by a range of factors, including directional scattering (both forward and backward), multiple scattering, particle diffusion, fouling or deposition on optical windows, air-flow fluctuations, and variations in gas temperature. Previous studies, such as those involving on-stack transmissometer systems, have modified optical designs to reduce the influence of lateral scattering and internal reflections (Beutner, 1974). Beyond simple direct-transmission approaches, some systems apply dual-wavelength absorption or multi-angle measurement techniques to achieve more accurate correction of scattering effects and background contributions.

2.2 Digital Optics System Framework (DOEF) Ringlemann

The proposed system architecture consists of several integrated components designed to enable robust and objective optical assessment of smoke opacity. First, the illumination subsystem employs a monochromatic or narrow-band light source, typically centered around a wavelength of approximately 550 nm in the green spectral region. This choice is motivated by the high photopic sensitivity of the human eye in this band, which aligns well with the perceptual basis of the Ringlemann scale. As an alternative, broadband LEDs equipped with bandpass optical filters, or low-power laser sources combined with mild optical diffusion to suppress coherence effects, may be used to ensure spectral stability and measurement consistency.

The optical path is established by installing two optical windows on opposite sides of the stack or duct, with careful mechanical alignment to ensure that the light beam traverses the central region of the smoke column. The optical path length is selected according to the stack diameter and typically ranges from about 0.5 m to several meters, providing sufficient sensitivity across a wide range of opacity levels.

For signal acquisition, the system may employ silicon photodiodes characterized by high linearity over the relevant intensity range, enabling reliable photometric measurements. Complementarily, digital cameras based on CCD or CMOS sensors can be used to capture two-dimensional images of the smoke plume, allowing spatial analysis of opacity variations across the flow cross-section.

Image processing and calibration are carried out within a dedicated computational module. Acquired RGB images are converted into alternative color spaces such as HSV or YUV, from which luminance-related channels (the V or Y channel) are extracted. The measured intensities are then normalized against reference conditions obtained in the absence of smoke, thereby minimizing the influence of external illumination variability. Relative intensity values are subsequently mapped to equivalent Ringlemann levels using regression models, which may be linear, polynomial, or nonlinear depending on the observed response characteristics. Additional adaptive correction algorithms can be incorporated to compensate for background fluctuations, such as changes in sky brightness or cloud cover.

Finally, system calibration and validation are performed under controlled conditions using simulated smoke with varying particle densities generated by smoke or aerosol generators. At each density level, trained observers provide reference Ringlemann scores through visual assessment, which are used to establish the mapping function between relative optical intensity and Ringlemann grade. The resulting model is evaluated through cross-validation and statistical performance metrics, including mean squared error (MSE), coefficient of determination (R^2), and mean absolute deviation, to ensure accuracy, robustness, and reproducibility of the proposed measurement system

3. Analysis and Discussion

3.1 Enhancement Using Machine Learning and Image Segmentation Techniques

To address the challenges posed by variable backgrounds and real-world environmental conditions, the integration of machine learning techniques is highly relevant and increasingly adopted in recent studies. Rather than relying solely on fixed thresholds or global intensity measures, data-driven approaches enable adaptive and context-aware interpretation of smoke imagery.

One widely used strategy is smoke segmentation, or pixel-level masking, in which smoke regions are explicitly separated from the background. Deep learning–based semantic segmentation models, such as DeepLab v3+, have proven effective in isolating smoke pixels under complex background conditions. Recent studies have demonstrated that architecture such as W-Net and DeepLab v3+ can be employed to automatically estimate smoke opacity by analysing only the segmented smoke regions, thereby significantly reducing background interference and improving measurement reliability (Park et al., 2024).

Another approach involves object detection and bounding-box–based analysis. In this framework, convolutional neural networks such as YOLOv5, often enhanced with attention mechanisms, are used to detect smoke plumes and define regions of interest. The opacity or darkness level is then computed within the detected bounding boxes. Applications of this method to ship exhaust monitoring have reported promising results, with YOLOv5s-CMBI combined with Ringelmann-based grading achieving classification accuracies of approximately 92.1% under real operational conditions (Wang et al., 2023).

Beyond detection and segmentation, nonlinear regression and deep learning models can be employed to directly map optical features—such as mean intensity, contrast, or intensity histograms—to equivalent Ringelmann scores. These mappings may be implemented using multilayer perceptrons (MLPs), support vector regression (SVR), or ensemble-based regression methods, allowing the system to capture nonlinear relationships between visual characteristics and perceived opacity.

Importantly, machine learning models can be trained on datasets encompassing diverse weather conditions, viewing angles, and background scenarios. This enables the implementation of adaptive correction mechanisms that enhance robustness against environmental variability, making the overall system more reliable and suitable for long-term deployment in real-world monitoring applications.

3.2 Experimental Procedure and Evaluation

The experimental evaluation of the proposed system is conducted through a combination of controlled laboratory tests and field-based validation. Initially, a smoke chamber or a miniature stack duct is constructed to provide a controlled environment in which smoke density can be systematically varied. A range of smoke concentrations, for example from 0% to 100% opacity, is generated using a smoke or aerosol generator, while reference measurements are obtained either through analytical methods or visual assessment based on the Ringlemann scale.

During each experimental run, image data are acquired over defined time intervals, such as at frame rates of 1 fps or 10 fps, while photometric sensor readings are recorded simultaneously. These synchronized datasets form the basis for calibrating the mapping model that relates measured optical features to equivalent Ringlemann values. Model calibration is followed by validation tests under previously unseen scenarios, including extreme smoke densities and dynamically changing backgrounds, to assess robustness and generalization capability.

System performance is evaluated using standard statistical metrics, including the coefficient of determination (R^2), the root mean squared error (RMSE) between predicted and reference values, and the mean absolute deviation. Additional analyses are performed to quantify sensitivity to different operating conditions, such as low versus high ambient illumination, thereby ensuring that the system maintains acceptable accuracy across a wide range of environmental scenarios. Beyond laboratory-scale experiments, field testing under real operational conditions—such as industrial stacks or vehicle exhausts—is essential as a final stage of validation. These tests provide critical evidence of system reliability, practicality, and compliance with regulatory expectations.

Overall, the state of the art reveals a consistent shift from purely visual, score-based assessments toward standardized, image-based optical measurements, and further toward fully automated systems incorporating deep learning–based segmentation and detection. This technological evolution is accompanied by increasing integration of optical monitoring systems into industrial and maritime emission monitoring ecosystems.

From an industrialization perspective, research studies and technical reports published between 2020 and 2023 indicate growing interest in in-situ optical monitors integrated within Continuous Emission Monitoring System (CEMS) frameworks. For example, evaluations reported by organizations such as the Electric Power Research Institute (EPRI) demonstrate that in-situ optical monitors can be benchmarked against performance test procedures, such as relative accuracy test audits (RATA), and conventional CEMS data, with the objective of reducing operational and maintenance costs compared to complex extractive systems. Within a Ringlemann-based framework, this trend is particularly significant, as it provides a realistic pathway for adoption: outputs from optical–computational systems can be positioned as documented, real-time compliance indicators that are fully compatible with modern quality assurance and quality control (QA/QC) practices.

3.3 *Integration with CEMS and In-situ Optical Monitors (Industrialization Trend)*

In the maritime sector, increasing regulatory attention to ship exhaust emissions—particularly so-called *black smoke*—has accelerated the adoption of automated optical monitoring approaches. These systems typically rely on object detection and visual darkness assessment methods that are conceptually analogous to the Ringelmann scale. In this context, Wang et al. (2023) proposed a framework that combines plume detection using a YOLOv5-based architecture with attention mechanisms and multi-feature fusion, followed by quantitative evaluation of plume darkness using a Ringelmann Blackness–based grading method. Their results demonstrated high grading accuracy under operational conditions, while also highlighting persistent challenges associated with dark or highly variable backgrounds, which can degrade performance at higher darkness levels.

From a system design perspective, these findings provide important insights for the development of Ringlemann-based optical–computational frameworks. In particular, they emphasize the necessity of well-defined background reference regions and adaptive correction mechanisms to ensure measurement stability and robustness across diverse environmental and operational settings. Such considerations are critical when positioning optical opacity monitoring systems for integration into Continuous Emission Monitoring Systems (CEMS) and for broader industrial adoption during the 2019–2023 period.

3.4 *Extension to the Maritime Sector and Computer Vision–Based Emission Surveillance*

One of the most significant developments between 2018 and 2023 has been the systematic transfer of the *region-of-interest (ROI) selection* task from human operators to machine learning–based computer vision algorithms. Pedrayes et al. (2023) emphasized that many existing opacity estimation approaches still rely on manual selection of both plume regions and background reference areas, a requirement that introduces subjectivity and limits reproducibility. To address this limitation, they proposed deep learning–based networks capable of automatically identifying appropriate ROIs, thereby improving consistency and robustness across diverse industrial scenes.

Once ROIs can be determined automatically, the subsequent methodological advancement lies in semantic smoke segmentation. Techniques based on convolutional neural network architectures, such as the U-Net family or DeepLab variants, enable the isolation of smoke pixels from complex backgrounds, ensuring that darkness or contrast calculations are performed exclusively on physically relevant plume regions. This segmentation-driven approach has been shown to outperform simple intensity thresholding, particularly under conditions of heterogeneous backgrounds and variable illumination.

Another notable trend is the increasing focus on model compression and deployment on edge devices. Recent studies on smoke segmentation algorithms published in 2024 have identified DeepLabV3+ as a common baseline architecture, while explicitly addressing the trade-off between segmentation accuracy and computational efficiency required for real-time field deployment on resource-constrained hardware. Conceptually, the integration of semantic segmentation with nonlinear regression or learning-based mapping methods enables a more robust and direct transformation of image-derived features into equivalent Ringlemann scores, representing a substantial advance over traditional, heuristic intensity-based approaches

3.5 ROI Automation and Smoke Segmentation Using Deep Learning

Research conducted since 2015 has demonstrated that both still cameras and video systems can be used to estimate plume opacity with acceptable stability under field conditions, provided that background effects and calibration issues are addressed explicitly. Yuen et al. (2018) showed that the Digital Optical Method (DOM), which was originally developed for still photography, can be extended to camcorder-based systems, enabling near–real-time opacity estimation at frame rates of approximately 1 Hz. This work clearly identified background selection and plume–background contrast as dominant sources of uncertainty, highlighting region-of-interest (ROI) definition and background correction as critical design considerations.

Earlier findings by Yuen (2017) further indicated that camera calibration procedures can be simplified by exploiting camera exposure parameters, such as exposure value compensation. This approach is particularly relevant for low-cost implementations using compact cameras or smartphones. Within a Ringlemann-based framework, the DOM line of research is important because it effectively bridges the long-standing, human-perception–based notion of "darkness" with a quantitatively measurable parameter derived from image contrast.

3.6 Camera- and Video-Based Methods for Plume Opacity under Field Conditions

The broader scientific implication of this transition is that opacity is no longer treated merely as an observational score, but rather as a measurable quantity that can be derived from radiometric or photometric models and image-based contrast measurements. As a consequence, the primary sources of uncertainty shift from inter-observer variability to issues related to instrumentation and modeling, including exposure calibration, sensor dynamic range, optical stability (e.g., window cleanliness and optical alignment), and the consistent definition of regions of interest.

In regulatory practice, opacity assessment has historically relied on human observation, such as visible emission evaluations following EPA Method 9 or grading based on the Ringlemann scale. These approaches are inherently limited by observer subjectivity, dependence on ambient lighting conditions, and difficulties in documentation and retrospective auditing. Over the past decade, however, a significant shift has occurred toward digital image–based methods that offer greater objectivity and traceability. The standardization of the Digital Camera Opacity Technique (DCOT) through ASTM D7520 represents a key milestone in this transition, as it specifies procedures for image acquisition, background selection, calibration, and opacity computation based on image contrast. At the policy level, DCOT has also been recognized as an alternative to visual assessment under defined conditions, for example through alternative method approvals such as EPA ALT-082, thereby establishing a clearer pathway from subjective observation to data-driven, digitally verifiable measurement.

4. Potential Implementation and Qualitative Evaluation

4.1 Industrial and Field Applications

The proposed optical–computational framework offers broad applicability across industrial, transportation, and environmental monitoring contexts. One of the most direct applications is industrial stack monitoring, where an inline optical module installed across a stack or duct can provide continuous, real-time indications of smoke opacity. Such systems can be configured to trigger alarms when regulatory thresholds are exceeded, supporting proactive process control and compliance monitoring. Similar inline or in-situ optical approaches have been widely discussed in the context of modern Continuous Emission Monitoring Systems (CEMS), where they are valued for their ability to deliver continuous data with relatively low operational complexity compared to extractive methods (Jahnke, 2022).

A second important application is vehicle smoke testing, particularly in inspection and maintenance (I/M) programs. Miniaturized implementations—using compact optical sensors or smartphone cameras combined with embedded algorithms—can function as rapid qualitative screening tools in the field. In this context, captured smoke images can be processed on-site and directly converted into equivalent Ringlemann scores, providing inspectors with an immediate and standardized indication of excessive smoke emissions without the need for bulky instrumentation.

The maritime sector represents another promising domain of application. Recent research on ship exhaust monitoring has demonstrated that computer vision techniques, such as YOLOv5-based plume detection combined with Ringelmann-inspired darkness grading, can be used to assess black smoke emissions from vessels with high accuracy (Wang et al., 2023). These techniques can be deployed at ports, coastal observation points, or along shipping routes as part of maritime emission surveillance systems, complementing existing regulatory frameworks for ship emissions.

Finally, integration with **IoT and smart environment platforms** further enhances the practical value of the system. Opacity data streams can be linked to SCADA systems or cloud-based IoT infrastructures, enabling real-time visualization, automated reporting, and long-term trend analysis. Such integration aligns well with current developments in smart environmental monitoring, where distributed sensors and data analytics are increasingly used to support evidence-based regulation and decision-making.

4.2 Qualitative Testing and Field Validation

Beyond quantitative measurements, the system also has significant potential as a qualitative assessment and validation tool. It can serve as a rapid calibration aid when physical Ringlemann charts are unavailable, damaged, or impractical to deploy. In environmental audits, regulators may use portable optical devices as quick reference instruments to support visual judgments and provide documented evidence. Moreover, in remote or resource-limited regions, camera-based systems running on mobile devices can enable environmental inspectors to verify emission compliance without access to centralized laboratories or advanced instrumentation. Such use cases reflect the system's flexibility and its role as a bridge between traditional visual methods and fully instrumented monitoring systems.

4.3 Field Challenges and Mitigation Strategies

Despite its potential, field deployment of optical opacity monitoring systems faces several practical challenges. Variations in background illumination, such as changes in sky brightness or cloud cover, can introduce intensity errors; these effects can be mitigated through the use of internal reference measurements, adaptive background correction algorithms, or optical filtering. Particle deposition on optical windows may reduce signal transmission over time, necessitating automatic cleaning mechanisms (e.g., air or fluid purge systems) or the use of anti-deposition coatings. Smoke fluctuations and flow turbulence can cause short-term signal variability, which can be addressed through temporal averaging and signal filtering techniques.

Geometric factors also play a role: differences in viewing angle may introduce perspective distortion, requiring careful geometric calibration or the use of telephoto optics to stabilize the measurement geometry. Finally, long-term sensor drift and changes in optical characteristics underscore the importance of periodic recalibration, routine QA/QC procedures, and cross-calibration against reference methods.

Taken together, these considerations indicate that while optical–computational opacity monitoring systems are technically feasible and increasingly mature, their successful deployment depends on thoughtful system design, robust calibration strategies, and alignment with established quality assurance practices.

5. Conclusion

This paper has presented a comprehensive theoretical framework, methodological approach, and up-to-date review of optical technologies for smoke opacity monitoring based on the Ringlemann chart concept. Several key conclusions can be drawn from this study.

First, optical measurement techniques combined with image processing enable smoke opacity to be assessed in a manner that is more objective, continuous, and readily integrable with modern monitoring systems than traditional visual observation methods. Second, the integration of optical sensors, digital cameras, adaptive calibration procedures, and machine learning models significantly enhances system robustness against variations in background conditions and ambient illumination. Third, recent studies demonstrate that deep learning–based approaches, including smoke segmentation and object detection, can substantially improve opacity estimation accuracy under real-world operating conditions. Fourth, in-situ optical monitors have been evaluated within industrial emission monitoring frameworks, such as Continuous Emission Monitoring Systems (CEMS), and have shown performance comparable to reference methods while offering lower operational and maintenance costs. Finally, although practical deployment faces challenges—including background variability, optical window fouling, plume fluctuations, and the need for routine recalibration—these issues can be addressed through appropriate system design and mitigation strategies.

Based on these findings, several directions for future research are recommended. These include the development of deep learning algorithms that remain robust under extreme environmental conditions, such as rain, fog, and low-contrast backgrounds; extensive field experiments on full-scale industrial stacks under varying weather conditions and combustion loads; the design of miniaturized, energy-efficient, and modular devices to facilitate field deployment; deeper integration of optical monitoring systems with IoT platforms, big data analytics, and automated emission control systems; and, importantly, the standardization of methods, calibration protocols, and validation procedures recognized by regulatory authorities to support broader acceptance of optical opacity monitoring technologies in environmental compliance and enforcement.

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