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Article

Electrostatic precipitators in the era of smart technology: Electrical efficiency, vibration mitigation, and noise reduction

Junfeng Li[1,*], Yu Lu[1], Xinjiang Xu[1], Chunchun Sun[2], Qiliang Zhu[2], Dengke Zhao[2]

[1] CHN Energy Shenhua Jiujiang Company, Jiujiang 332500, China
[2] Zhejiang DOWAY Advanced Technology Co., Ltd., Hangzhou 310000, China
*** Corresponding author:** Junfeng Li, 16080274@ceic.com

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Abstract: Electrostatic precipitators (ESPs) are significant devices for particulate control in power generation, cement production, steel manufacturing, and other high-emission sectors. Future ESP performance should be evaluated not only on particle collection efficiency but also on electrical energy consumption, vibration stability, noise levels, reliability, and adaptive functionality. We proposed a three-layered framework for perception, analysis, and execution in intelligent ESPs. The perception layer combines electrical, emission, process, vibration, acoustic, and maintenance data; the analysis layer applies signal processing, artificial intelligence, digital twins, and multi-objective optimization; and the execution layer provides adaptive voltage control, rapping optimization, fan-speed control, vibration mitigation, active noise control, and predictive maintenance. The quantitative data show that intelligent electrical optimization can reduce ESP energy consumption by 35.50% and improve emission compliance from 95% to 100%. Approximately 43% energy saving was achieved by deep-learning-assisted voltage optimization in a 330 MW coal-fired power plant ESP. FFT, wavelet transform, RMS tracking, CNNs, LSTM models, and autoencoders can be used as diagnostic methods to detect imbalance, resonance, bearing faults, and fan irregularities, thereby reducing vibrations. Hybrid passive-active control for noise reduction can attenuate low-frequency duct noise by more than 10 dB and high-frequency components by more than 20 dB. This review highlights the absence of field-validated collaborative optimization as a significant knowledge gap and suggests digital twins, edge computing, 5G/6G communication, and multi-objective control as promising avenues for future research.

Keywords: electrostatic precipitators; smart technology; electrical efficiency; vibration mitigation; noise reduction

1. Introduction

Electrostatic precipitators (ESPs) have been widely used in power generation, cement, steel, and other particulate-emitting industries due to their ability to treat large volumes of gases at relatively low-pressure drop, high collection efficiency, and service life [1–4]. Their operation is based on the basic principle of corona discharge, particle charging, migration of charged particles toward collecting electrodes, and periodic removal of deposited dust from the collection surface. **Figure 1** illustrates the basic working principle of an ESP with the discharge electrode, charged particle trajectory, and collection plate arrangements [1–4]. ESPs are mature devices for pollution control, and the current challenge to ESPs is no longer only collection efficiency. The modern ESP must also operate with consideration for electrical energy consumption, mechanical vibration, acoustic emissions, equipment reliability, and maintenance costs.

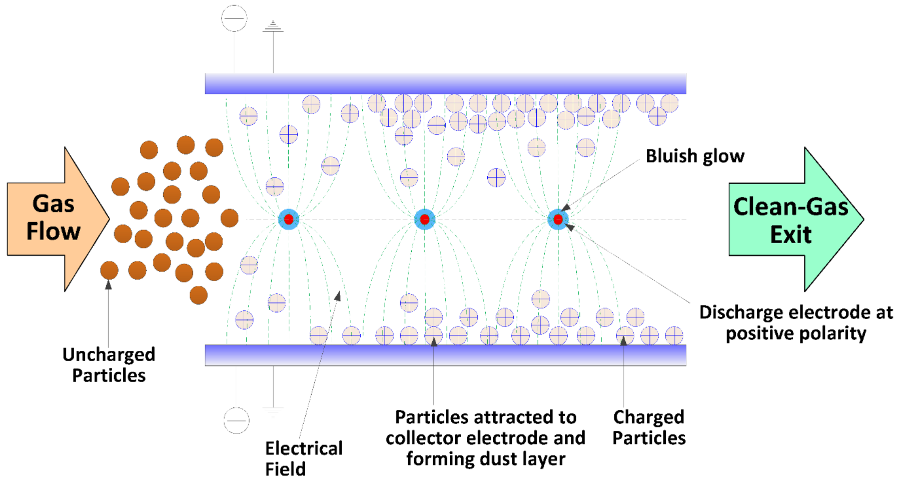

Figure 1. Basic working principle of an electrostatic precipitator, showing the corona discharge and particle collection process [1].

Electrical efficiency has become a major concern, as traditional ESPs are generally operated with conservative voltage and current margins to maintain emission compliance under varying gas flow, dust loading, humidity, and particle resistivity. This strategy can ensure stable operation, but may waste energy when the actual particulate load is low. A number of reports demonstrate a potential benefit from smarter control. ESPs can reach specific energy consumption below 0.3 Wh/m^3 in some applications [5]. Real-time intelligent optimization has been reported to achieve a 35.50% reduction in ESP energy consumption and a 95%–100% improvement in emission compliance under the same outlet concentration constraint [6]. In a 330 MW coal-fired power plant ESP, optimization based on long short-term memory prediction, an attention mechanism, and particle swarm optimization achieved an energy-saving rate of about 43% while maintaining dust emission requirements more recently [7]. The results suggest that the performance of ESP should be evaluated using energy-normalized and operation-adaptive indicators rather than dust-removal efficiency alone.

Mechanical vibration and noise are equally important, but less systematically included in ESP reviews. Vibration in ESP systems is mainly caused by induced-draft fans, motors, rotating equipment, support structures, gas flow turbulence, rapping devices, and electrostatic interactions [8–11]. Excessive vibration can cause increased bearing wear, loosening of structural connections, misalignment of electrodes, increased fatigue, and reduced collection stability. With the development of modern signal-processing methods such as fast Fourier transform, root-mean-square vibration velocity, wavelet transform, envelope analysis, and time-frequency analysis, vibration can be treated as a diagnostic signal for imbalance, misalignment, looseness, resonance, and bearing faults [9, 12, 13]. Similarly, fans, ducts, motors, transformer-rectifier units, gas-flow passages, and rapping systems contribute to ESP-related noise. Passive methods such as acoustic enclosures, silencers, duct lining, and vibration isolation are still useful, but low-frequency fan and duct noise frequently needs active or hybrid treatment. Active noise control uses a reference microphone, an adaptive controller, a secondary loudspeaker, and an error microphone to generate anti-phase sound. Algorithms like filtered-X least mean square and filtered-X affine projection allow for real-time acoustic adaptation [14]. Hybrid passive-active control of ventilation-duct systems, as in ESP auxiliary equipment, has resulted in attenuation of more than 10 dB in low-frequency bands and passive attenuation of more than 20 dB at higher frequencies [15].

We propose a three-layered perception-analysis-execution architecture for smart ESPs. The perception layer contains sensors for voltage, current, spark rate, dust concentration, gas flow, temperature, humidity, vibration, sound pressure, and equipment condition. The analysis layer uses signal processing, statistical diagnosis, artificial intelligence (AI), digital twins, and multi-objective optimization to convert these signals into operational knowledge [16–20]. The execution layer transforms analytic results into adaptive voltage control, pulse energization, fan-speed regulation, rapping optimization, vibration suppression, active noise control, and maintenance scheduling [7]. Such an architecture combines electrical, mechanical, acoustic, and data-driven functions into a closed-loop system and yields a more well-defined classification view than separating sensors, artificial intelligence, and predictive maintenance into distinct technologies [21,22].

This review is unique in integrating electrical efficiency, vibration mitigation, and noise reduction in this unified smart-control framework. Previous research has focused on particle charging, electrode shape, power supply design, collection efficiency, or emission-control performance [1,5,6,23,24], while vibration analysis, acoustic control, and IoT-enabled maintenance have often been discussed separately [9, 11, 12, 25–27]. But in practice, ESPs are heavily cross-coupled: variations in voltage regulation affect spark behavior; rapping affects both dust re-entrainment and vibration; fan-speed control affects pressure drop and noise; and acoustic or structural changes can alter airflow resistance. Thus, future ESP development should be based on collaborative optimization rather than isolated subsystem improvement. Thus, we critically discuss the strategies for electrical efficiency, the sources of vibration and their mitigation, passive and active noise-control techniques, and system-level integration pathways for smart ESPs. The goal is to provide a framework for designing ESPs that are electrically efficient, mechanically reliable, acoustically safer, and operationally adaptive.

2. Electrical efficiency in electrostatic precipitators

Electrical efficiency in electrostatic precipitators is the ability to maintain the required particulate-matter removal performance with the minimum required electrical and auxiliary energy input. In conventional ESP operation, voltage and current are often set with conservative margins to prevent emission exceedance under varying gas flow, dust loading, particle resistivity, humidity, coal quality, and rapping disturbance. This approach increases the reliability of compliance but may result in unnecessary corona power consumption when the actual particulate load is low or when the individual electric fields need not be energized to their maximum levels. Therefore, electrical efficiency should not be seen merely as reducing voltage, but rather as balancing collection efficiency, power consumption, spark stability, dust re-entrainment, ozone generation, and outlet emission constraints [5,6,24,28–30].

2.1. Energy consumption mechanisms in ESP operation

The electric power consumption of an ESP is mainly attributable to the high-voltage power supply, corona discharge, electric-field formation, and auxiliary components such as rapping systems, heaters, control units, and induced-draft fans. The transformer-rectifier or high-voltage power supply converts low-voltage alternating current into high-voltage direct current that energizes the discharge electrodes and produces the corona ions needed to charge particles. The electric field then drives the charged particles to move toward grounded or oppositely charged collecting plates. In this process, the applied voltage, secondary current, corona onset voltage, spark limit, electrode spacing, gas velocity, and particle resistivity collectively determine the actual power demand [5,6,24,30].

An important characteristic of ESP energy consumption is its nonlinear relationship with collection performance. As the applied voltage increases, particle charging and migration increase, but the incremental improvement in dust removal decreases as the electric field approaches the spark or back-corona limit. Hence, the maximum voltage is not necessarily the most energy-efficient. The problem is more complicated in multi-field ESPs because the upstream, middle, and downstream fields do not contribute equally to the final outlet concentration. Early fields may strip large fractions of particles; later fields may just polish residual dust. Applying the same conservative voltage strategy to all fields can waste energy and may increase spark frequency or re-entrainment during rapping [6,31].

Another advantage of ESPs over many filtration options is that the electrostatic force acts directly on the particles, without requiring the entire gas stream to pass through a dense filter medium. Specific energy consumption below 0.3 Wh/m^3 has been reported for ESPs in small-scale combustion applications, whereas fabric filters and scrubbers have been reported at around 1 Wh/m^3 and 10 Wh/m^3, respectively [5]. However, this advantage can only be fully realized when the electric field, power supply, and control strategy are matched to real operating conditions.

2.2. Conventional energy-saving strategies

Traditional approaches to improving ESP electrical efficiency include electrode optimization, high-frequency power supplies, pulse energization, intermittent energization, spark-rate control, power-factor improvement, and field-by-field voltage regulation [24, 29, 30]. High-frequency high-voltage supplies can respond faster to load changes than conventional 50/60 Hz transformer-rectifier systems and can reduce voltage ripple, improve corona stability, and allow more precise control of secondary voltage and current. Pulse and intermittent energization are particularly useful under high-resistivity dust conditions because they can reduce back corona and improve particle charging while avoiding continuous excessive power input [30,32].

Field-by-field control is another important strategy. In a multi-stage ESP, each electrical field can be treated as a controllable unit with its own contribution to particle removal and energy consumption. Instead of operating all fields near the spark limit, the power distribution can be adjusted based on the inlet dust concentration, the outlet emission target, the gas flow, and field conditions. This strategy is especially relevant when rapping temporarily increases outlet dust concentration or when load changes alter residence time. However, conventional proportional-integral-derivative (PID) or manual control may not locate the true optimum because the ESP process is nonlinear, delayed, and strongly coupled [6,31].

Electrode geometry and surface condition also influence electrical efficiency. Wire-plate spacing, discharge-wire shape, collection-plate distance, field strength, dust layer condition, and gas distribution determine the voltage-current characteristics of each field. Industrial case analysis has shown that knowing the real current-voltage characteristics of ESP sections is important for automation because the measured behavior reflects the combined effects of geometry, temperature, humidity, dust composition, gas composition, and electrode condition [33]. It means that practical electrical optimization should combine theoretical models with site-specific measurements rather than relying only on design values.

2.3. Smart voltage/current optimization and adaptive control

Smart ESP control shifts the focus of electrical efficiency improvement from fixed operating rules to data-driven, model-based optimization. The basic idea is to use online measurements, such as secondary voltage, secondary current, spark rate, boiler load, flue gas flow, temperature, humidity, opacity, and outlet dust concentration, to determine the minimum energy input required to meet emission limits. In the perception-analysis-execution framework proposed here, the perception layer is formed by voltage, current, and emission sensors; the analysis layer by prediction and optimization algorithms; and the execution layer by power-supply set-point adjustment.

An example of this is experimental set-ups for testing the collection efficiency of electrostatic precipitators in controlled environments, which need the core treatment unit to be coupled with accurate auxiliary flow and diagnostic instrumentation. **Figure 2** illustrates such an integrated testing loop [34]. The physical movement and generation of the emission stream necessitate a particulate dosimeter (1) for the aerosol supply and a ventilator (5) to induce the draft through the system. The diagnostic and analytical capabilities of the bench are entirely contingent on the integrated monitoring instrumentation. In particular, the flow dynamics inside the vertical duct are continuously monitored by an in-line air velocity sensor (4) and high-precision optical particle tracking sensors (3) are installed upstream and downstream of the ESP (2) for the measurement of real-time particle size distributions and fractional removal efficiency.

Many algorithms are related to smart electrical optimization. Genetic algorithms (GAs) can be used to search for optimal secondary-voltage combinations in multi-field ESPs to minimize total power while meeting outlet concentration constraints. In the GA-based study on a factual multi-stage ESP, the secondary voltage and outlet concentration relationship was modeled by an RBF neural network, the voltage-current and voltage-power relationships were described by polynomial fitting, and GA was used to identify the optimal secondary voltage for each field [31]. The application reduced total power by about 16 kVA, 8 kVA, and 18 kVA under three outlet concentration limits while still satisfying the required dust concentration constraints [31].

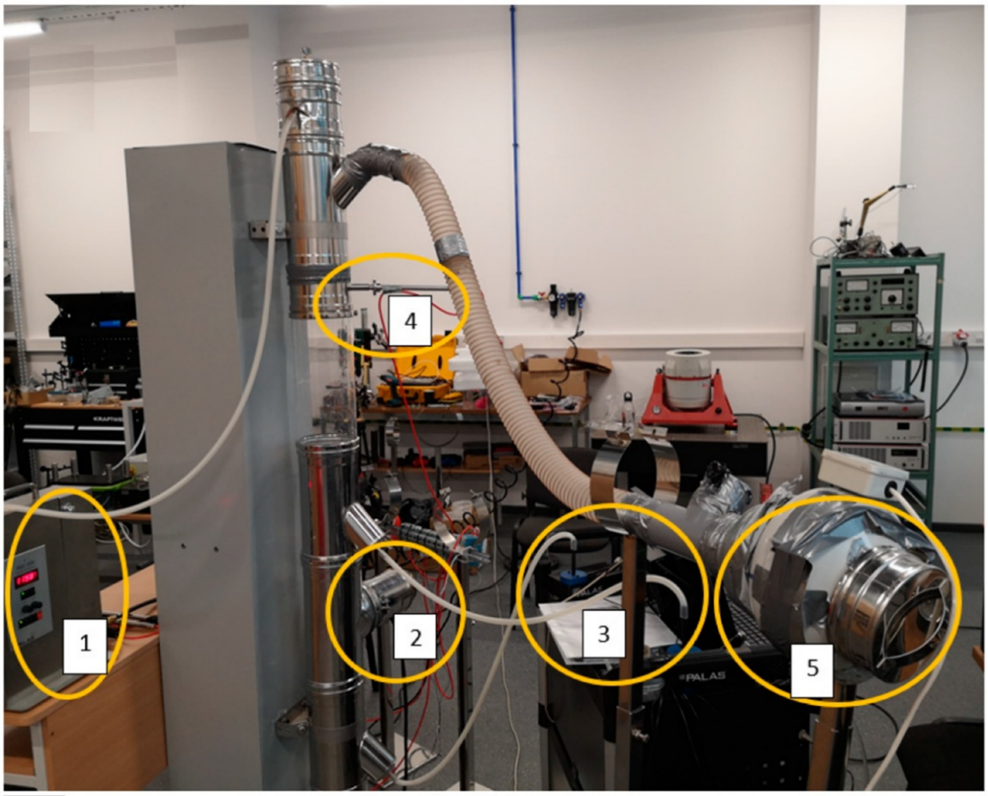

Figure 2. Experimental configuration of the bench for the determination of the efficiency of removal of particulate matter in an ESP system. The labels describe the whole process flow and embedded diagnostic instrumentation: (1) Palas RGB 1000 aerosol generator used for controlled PM injection. (2) The electrostatic precipitator test unit. (3) Online optical particle tracking sensors (Welas digital 3000) for pre- and post-treatment concentration analysis. (4) An inline gas flow velocity sensor (MKA880). (5) A ventilator for system exhaust. Source: Adapted from Sokolovskij et al. [34].

Another suitable method is particle swarm optimization (PSO), since the ESP operation is a multi-variable, nonlinear, constrained optimization problem. In a real-time intelligent optimization system (IOS), a prediction model is used to estimate outlet concentration, an optimization module is used to solve the minimum-energy problem, and a coordination module is used to adjust set points based on real-time operating data and rapping disturbance [6]. Compared with manual and PID operation, this IOS improved emission compliance from 95% to 100%, moved the median concentration 46.6% closer to the target emission, and achieved 35.50% energy saving under the same emission upper limit of 30 mg/m^3 [6]. This shows that prediction, optimization, and closed-loop execution lead to improved electrical efficiency while meeting emission compliance.

Deep learning methods further improve smart ESP control by addressing time delays and temporal correlations. The outlet dust concentration does not respond immediately to changes in voltage or flue gas because the particles require residence time to pass through several chambers and electric fields. Long short-term memory (LSTM) networks are well-suited for this problem, as they can capture temporal dependencies in sequential operating data. A combined mechanism-based voltage-current model and an LSTM model with an attention mechanism were used to predict outlet dust concentration, and the secondary voltage was recently optimized using PSO. The voltage-current model had a mean absolute percentage error of 1.43% in a 330 MW coal-fired power plant; the outlet concentration prediction model obtained a mean absolute percentage error of 5.2% in the testing set, and the optimization experiment achieved about 43% of energy saving with an estimated annual carbon reduction of about 2,621.34 t for 300 operating days [7].

For plants already in operation, another practical option is adaptive feed-forward control. This approach employs solid particulate matter or opacity signals as feedback or feed-forward inputs to modify the current setting of the corresponding transformer-rectifier field. In a study of a thermal power plant, smoke/opacity information was used to adapt the controller gain. It was reported that adaptive control reduced SPM values compared to conventional control. Representative 1:1 pulse-rate values were decreased from approx. 45–49 mg/m^3 to about 20.5–29.1 mg/m^3 [35]. Although this evidence is less comprehensive than the IOS and deep-learning cases, it illustrates how additional emission feedback can improve field-level electrical control in legacy ESP systems.

2.4. Quantitative comparison of traditional and smart ESP operation

The evidence presented suggests that the intelligent electrical optimization of the ESP can provide quantifiable benefits over manual or conventional control. Conventional manual operation is usually at steady but conservative voltages, keeping the outlet concentration below the target but often well below the allowable limit, wasting power. PID control can respond automatically, but it may fluctuate under rapping or disturbances and may not coordinate different fields well. In contrast, smart optimization systems can be operated closer to the emission target while remaining compliant, thus reducing unnecessary corona power [6].

The quantitative range available in the literature is large. Representative quantitative evidence for conventional, optimized, and smart electrical-efficiency strategies for ESPs is summarized in **Table 1**. The specific energy consumption of ESPs is already low compared to other particle control technologies, with reported values below 0.3 Wh/m^3 for small-scale combustion applications [5]. Real-time IOS operation achieved 35.50% energy conservation under an emission upper limit of 30 mg/m^3 [6]. GA-based optimization of a multi-field ESP reduced total power by 8–18 kVA across different outlet concentration limits [31]. Deep learning-assisted optimization in a 330 MW coal-fired unit brought energy savings of nearly 43% and estimated annual carbon emission reductions of about 2,621.34 t [7].

Table 1. Quantitative evidence and algorithmic pathways for improving electrical efficiency in conventional and smart ESP operation.

Approach/strategy	Context	Core technical method	Quantitative performance	Smart design implication
Baseline Advantage	Small-scale combustion [5]	Charging & low-ΔP particle collection	Energy consumption: 0.3 Wh/m^3 Fabric filters: ~1 Wh/m^3 Scrubbers: ~10 Wh/m^3	Inherent energy efficiency relies heavily on dynamic voltage and airflow optimization.

Table 1. *Cont.*

Approach/strategy	Context	Core technical method	Quantitative performance	Smart design implication
Dielectric-Coated Electrodes	Lab scale; commercial duct type [36]	Coating, narrow plate spacing, high field strength	Filtration: Comparable to F7 filter Energy: ~85% lower than F7 Ozone: 5.9 ± 2.2 mg/h 2–7 lower than uncoated	Co-evaluation of filtration, pressure drop, and ozone generation is vital.
Real-Time Intelligent System	Industrial; ultra-low-emission [6]	Online outlet prediction, adaptive set-point adjustments	Compliance: Increased from 95% to 100% Target error: Reduced by 46.6% Energy savings: 35.50% (at 30 mg/Nm^3 limit)	Coupling emission prediction with power supply ensures simultaneous compliance and savings.
Multi-Field GA Optimization	Multi-stage industrial application [31]	RBF neural network modeling, V-I fitting, Genetic Algorithm	Power reduction: 16, 8, and 18 kVA under 50, 40, and 30 mg/Nm limits, respectively	Non-uniform, field-by-field voltage allocation optimizes energy under fixed constraints.
Deep Learning Voltage Optimization	330 MW coal-fired power plant [7]	V-I mechanism model, LSTM with attention, PSO	Model MAPE: 1.43% (V-I), 5.2% (outlet) Energy savings: ~43% CO_2 reduction: ~2,621.34 t/year	Physics-informed temporal deep learning enables robust control under dynamic loads.
Adaptive Feed-Forward Control	Thermal power plant [37]	Opacity/SPM feedback, adaptive pulse-rate tuning	SPM emissions: Decreased from 45–49 mg/m^3 (conventional) to 20.5–9.1 mg/m^3	Legacy units can be successfully retrofitted via emissions-feedback loops.

Note: ΔP, SPM, PSO and MAPE are pressure drop, suspended particulate matter, particle swarm optimization and mean absolute percentage error, respectively.

The table shows that the greatest improvements in electrical efficiency are achieved when the power supply control is coupled with real-time emission prediction, field-level optimization, and operating-condition feedback. However, the reported studies vary in terms of plant scale, emission limits, gas-flow conditions, and performance metrics. Future ESP studies should report energy use with outlet concentration, compliance rate, field configuration, and operating constraints [5–7,31,36,37]. In addition to **Table 1**, we have visualized the data to demonstrate the improvements in energy usage and emissions stability with smart ESP control. **Figure 3** shows comparison of conventional/manual control, PID-based operation, real-time intelligent system (ISO) optimization, GA-based field-level optimization, and deep-learning-assisted particle swarm optimization (DP/PSO) based on the reported energy-saving and compliance indicators [6,7,31].

2.5. Limitations and prospects in electrical optimization

However, there are still some limitations in the development of smart electrical control. Many studies report energy savings under different plant sizes, dust loads, flow rates, emission limits, and power-supply configurations, making direct comparison difficult. A standardized reporting format is required with gas flow, inlet and outlet dust concentrations, emission limits, field number, voltage/current ranges, spark rate, and energy consumption. The trade-off between energy saving and long-term reliability has not yet been well quantified. Lower voltage may reduce power consumption but increase dust accumulation if the collection margin becomes too small. High voltage may improve instantaneous collection but increase sparking, re-entrainment, ozone production, and electrode aging [5,36].

Most optimization studies concentrate on electrical variables and do not fully consider mechanical and acoustic consequences. In practice, voltage control may interact with rapping intensity, dust re-entrainment, fan load, vibration, and noise. Hence, future research on electrical efficiency should be combined with multi-objective optimization, considering emission compliance, power consumption, vibration, noise, maintenance risk, and carbon reduction simultaneously. Finally, many AI-based models are trained on site-specific historical data, which can limit their transferability across plants. Transfer learning, physics-informed machine learning, digital twins, and edge-cloud collaborative optimization may improve the robustness of the model under the changing coal quality, deep peak regulation, biomass blending, and ageing of equipment [7].

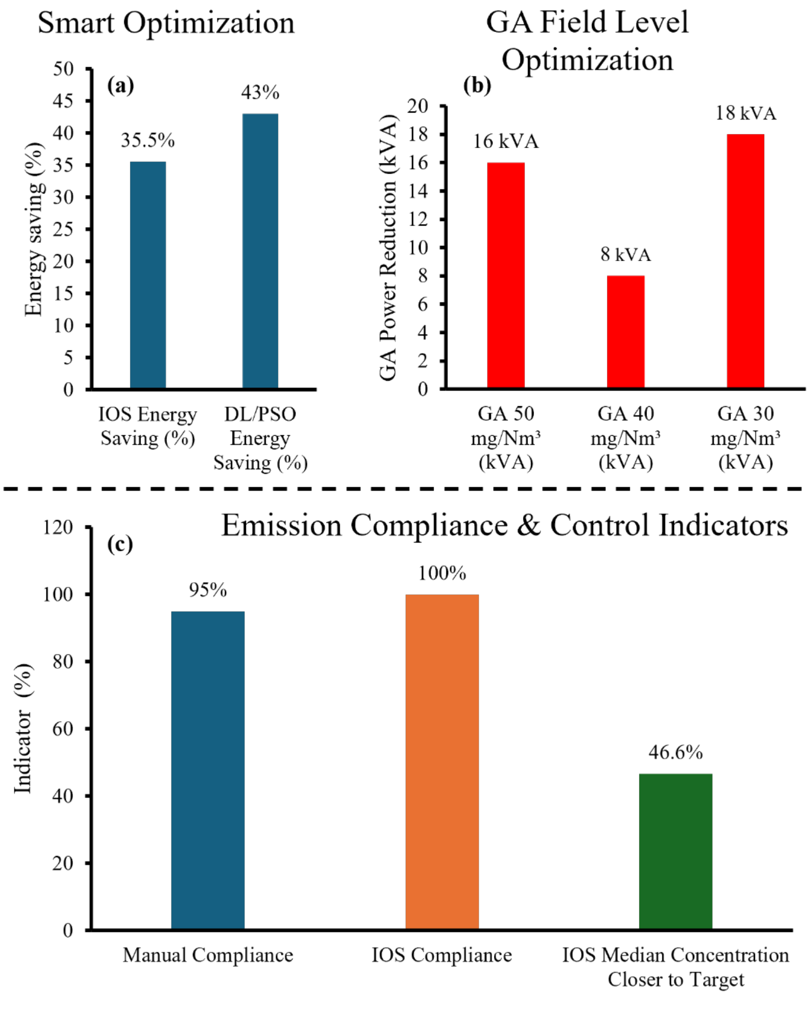

Figure 3. Quantitative comparison of the improvement in electrical efficiency in optimized and smart ESP operation: **(a)** Comparisons of the reported energy-saving performance from real-time intelligent optimization system (ISO) and the deep-learning-assisted particle swarm optimization DL/PSO optimization; **(b)** Multi-dimensional voltage optimization using GA; **(c)** Comparison of emission-compliance indicators of conventional/manual and intelligent optimization control.

Note: The GA values are expressed as power reduction for a given outlet concentration limit.

Source: Data are summarized from Zheng et al. [6] (ISO), Zhu et al. [7] (DL/PSO), Li et al. [31] for **(a)**, **(b)** and **(c)**, respectively.

Generally, the electrical efficiency in smart ESPs is shifting from hardware-centric improvement to integrated cyber-physical optimization. The best evidence shows that adaptive, real-time, and AI-assisted control can reduce energy consumption while maintaining or improving compliance with emissions standards. However, the next step in development should go beyond single-objective voltage optimization and move towards cooperative optimization among the electrical, mechanical, acoustic, and maintenance subsystems.

3. Vibration mitigation in electrostatic precipitators

In electrostatic precipitators, the vibration is mainly induced by induced-draft fans, motors, rotating shafts, bearings, rapping systems, support structures, gas-flow turbulence, and electrostatic interactions between charged particles and collection components [8–11]. ESP vibration is different from general structural vibration and has mechanical and process-related implications. It can accelerate fatigue damage, loosen bolted connections, disturb electrode alignment, increase bearing wear, reduce rapping regularity, and promote dust re-entrainment. Therefore, vibration mitigation in modern ESPs cannot be considered solely in terms of mechanical isolation. It can be viewed as a condition-monitoring, fault-diagnostic, and control problem for collection efficiency, maintenance scheduling, and operational reliability.

3.1. Major vibration sources in ESP systems

The most frequent causes of vibration in ESP installations are reciprocating and rotating components. Vibration is caused by imbalance, misalignment, looseness, eccentricity, rubbing, resonance, and bearing defects in fans, motors, gearboxes, couplings, shafts, and bearings [11,38]. These faults tend to produce specific frequency components associated with shaft speed, blade-passing frequency, bearing defect frequency, and harmonic responses. These vibrations are then transmitted to ESPs through ducts, platforms, support frames, casing walls, and electrode assemblies. When these frequencies are close to the structure's natural frequencies, resonance can amplify displacement and stress, increase the risk of fatigue, and shorten the equipment's life.

Another major source of vibration is rapping systems. Mechanical rapping is necessary to remove dust from the collecting plates and discharge electrodes. However, excessive rapping or rapping at the wrong time can cause transient structural impacts, electrode oscillations, re-entrainment of dust, and uneven cleaning. Finite element and transient dynamic analyses of rapping systems show that the hammering force, electrode geometry, rapper location, and structural stiffness are the main factors that affect the transmission of vibration and cleaning effectiveness [39]. Industry data indicate that rapping behavior, especially in the outlet field, produces the greatest fluctuations in particulate concentration. To ensure emissions compliance, advanced four-layer Intelligent Optimization Systems (IOS) are needed. These IOS solutions use coordination control logic to adaptively adjust operating voltages during transient rapping events, providing a way to stabilize performance [6]. Adamiec-Wójcik presented the modelling of the ESP rapping system, with the suspension and brushing bars using the rigid finite element method and the collecting plates using a hybrid finite element model, and showed that dynamic analysis of collecting-electrode vibration can be included in the design phase rather than only evaluated after installation [40]. Therefore, rapping should be optimized not only for dust removal but also for vibration control and structural durability.

Gas-flow-induced vibration is also applicable, especially in large ESPs operating under variable load. Panels, internal frames, and electrode systems can be excited by turbulent flow, non-uniform velocity distribution, vortex shedding, and duct pressure fluctuation. In some wet or vibrating precipitator configurations, controlled vibration has been used to improve particle capture. For example, a vibrating precipitator operating in resonance mode showed a 57% increase in particulate collection efficiency over a non-resonance condition [41]. This result is important because it shows that vibration is not always detrimental; the engineering challenge is to distinguish harmful uncontrolled vibration from useful controlled vibration.

3.2. Effects of vibration on ESP reliability and collection stability

Excessive vibration can degrade the performance of an ESP through several mechanisms. Electrode displacement modifies the local distribution of electric fields and could affect the uniformity of particle charging and migration. Misalignment between the discharge and collecting electrodes may increase the likelihood of sparking and result in unstable collection performance. Furthermore, vibration of the collecting plates may cause unintended dust detachment, resulting in re-entrainment before the scheduled rapping cycle. Repeated vibration can also cause fatigue in electrodes, frames, insulators, hoppers, and support members, increasing the chances of unplanned shutdowns [8–10].

Such a reliability problem is particularly critical for the collecting-plate rapping system, where the vibration is intentionally induced, but must be maintained within a safe mechanical range. Neyestanak et al. demonstrated that about 100 g of acceleration may be necessary to remove the deposited dust cake from the ESP collecting plates, and also that repeated impacts of the rapping hammer can generate dynamic stress concentrations in the rapping hammer and collecting plates. Numerical and experimental analyses have shown that rapping-induced acceleration is nonuniform across the collecting-plate assembly. Microscopic examination has shown fatigue features in the rapping hammer and corrosion-related voids and cracking in collecting plates. The results indicate that the optimisation of rapping should not only aim at maximizing dust detachment but also at controlling impact energy, acceleration distribution, stress concentration, and fatigue durability [42].

The vibration effect might be indirect. A fan or bearing defect may not immediately affect ESP collection efficiency, but can affect airflow rate, pressure distribution, gas residence time, and acoustic emission. Similarly, a poor rapping sequence may be viewed as a mechanical problem, but it can lead to spikes in outlet dust and unstable compliance with emission limits. This is why vibration monitoring should be integrated with electrical and emission monitoring rather than treated as a separate mechanical maintenance activity.

3.3. Signal processing and fault diagnosis for ESP-related vibration

Good vibration control starts with good vibration measurement and good signal interpretation. Common sensing devices include accelerometers, velocity transducers, displacement probes, and wireless vibration sensors, which are installed on fan housings, motor bearings, gearbox supports, rapping devices, and structural frames. The most commonly used diagnostic indicators are root-mean-square vibration velocity, peak acceleration, displacement amplitude, crest factor, kurtosis, and spectral peaks in the frequency domain [11,38].

The Fast Fourier Transform (FFT) is the fundamental tool for converting time-domain vibration signals into frequency spectra. It is useful to detect imbalance, misalignment, looseness, resonance, and bearing faults when characteristic frequencies are stable [11]. However, ESP operating conditions are often load-, rapping event- and gas-flow-dependent. Therefore, time-frequency methods are also needed. The short-time Fourier transform (STFT) can track frequency changes over time, and the wavelet transform can identify transient effects and non-stationary vibrations from rapping, flow disturbances, or bearing defects [9, 11]. Envelope analysis is useful for detecting rolling-element bearing faults by extracting modulated high-frequency impacts from the raw vibration signal. When the rotational speed varies, order tracking can be applied so that vibration components can be interpreted with respect to shaft order rather than a fixed frequency.

Beyond signal processing techniques, structural modelling is required to determine whether the identified vibration frequencies correspond to damaging plate modes or to acceptable rapping-induced motion. Finite element-based modal analysis can be used to determine natural frequencies and mode shapes of ESP collecting plates, and harmonic response analysis can be applied to the estimation of the acceleration at different locations on the plates under cyclic or impact excitation. Shinde et al. used CATIA-based modelling and ANSYS analysis of ESP collecting electrodes, and conducted modal analysis to determine the natural frequency and harmonic analysis to predict acceleration. Their comparison of the finite-element results with accelerometer-based physical measurements indicates that FEA can serve as a useful design-stage tool for estimating the collecting-plate vibration prior to costly field testing [43].

Machine learning methods can further improve fault diagnosis. The CNNs can classify the vibration spectra or time-frequency maps into fault categories, including imbalance, misalignment, bearing defect, or looseness. Long short-term memory networks can capture temporal degradation trends, and autoencoders can learn normal vibration patterns; anomalies can then be identified when reconstruction error exceeds an adaptive threshold. An LSTM-autoencoder framework has been proposed for induced-draft fan anomaly detection in power-plant auxiliary equipment, demonstrating its ability to provide early warning for rotating equipment related to ESP operation [44]. Such approaches are particularly useful when fixed thresholds are insufficient, as vibration signals vary with load, temperature, airflow, and operating regime. As a result, the vibration section should be made more technically explicit by linking the main vibration sources in ESP systems to measurable indicators, diagnostic signal-processing techniques, and corresponding mitigation actions. **Table 2** summarizes the main sources of vibration, recommended monitoring indicators, signal processing or AI methods, and practical mitigation strategies with respect to smart ESP operation [9,11–13,39,44].

Table 2. Vibration sources, diagnostic indicators, signal-processing methods, and mitigation strategies for smart ESP systems.

Subsystem/source	Measurable indicators	Analytical methods	Diagnostic purpose	Mitigation & execution strategy	References
ID Fans, Motors & Couplings	v_{RMS} (mm/s), a (m/s^2), x (μm); Shaft rotational frequency & harmonics.	FFT, order tracking, RMS trends, spectrum comparison	Identify: Imbalance & misalignment; Looseness & eccentricity; Rotating instability.	Dynamic balancing & shaft alignment; Bearing inspection & speed tuning; Structural stiffening & alarms.	Lutfullaeva [11], Moutsopoulou et al. [12], Clair [38]
Bearings & Gearboxes	High-frequency a peaks; Crest factor & kurtosis; Envelope spectrum/defect f.	Envelope analysis, FFT, WT, time-frequency, CNN	Early detection of: Bearing defects & local faults; Lubrication failure; Gear wear.	Bearing replacement; Lubrication correction; Gearbox inspection; Predictive maintenance scheduling.	Lutfullaeva [11], Moutsopoulou et al. [12], Hu et al. [44]
Rapping Systems & Collecting Electrodes	Transient a & impact amplitude; Electrode displacement (x); Dominant, f, decay time.	Transient dynamic analysis, FEA, time-domain impact response, WT	Evaluate: Rapping force transmission; Electrode fatigue; Collection vs. re-entrainment.	Rapping force/timing optimization; Rapper position adjustments; Electrode stiffness upgrades.	Maheshwaran [39]
Casing, Structural Frames & Platforms	Structural displacement (x); Panel vibration & resonance, f; Modal response.	Modal analysis, FEA, frequency response, STFT	Detect: Structural resonance; Fatigue-prone members; Weak zones & transfer paths.	Structural reinforcement; Tuned mass dampers (TMD); Damping treatments & isolation mounts.	Chu et al. [9], Moutsopoulou et al. [12], Dharmajan and AlHamaydeh [13]
Gas-Flow-Induced Vibration	Pressure fluctuations; Broadband vibration; Vortex-shedding frequency.	STFT, WT, flow-structure correlation, operational modal analysis	Identify: Turbulence-induced vibration; Flow maldistribution; Load-related instability.	Flow-straightener optimization; Duct design modifications; Fan-speed control & aero-smoothing.	Lutfullaeva [11], Moutsopoulou et al. [12], Dharmajan and AlHamaydeh [13]
Vibration-Assisted Precipitation	Resonance, f & mode shape; Oscillation amplitude; Collection efficiency variation.	Resonance analysis, amplitude-frequency analysis, experimental testing	Isolate: Beneficial controlled vibration vs. harmful uncontrolled anomalies	Controlled excitation tuning; Resonance & boundary control; Safe vibration limits enforcement.	Takacs [32]
Smart Vibration Monitoring Platform	Multi-sensor features Residual errors & anomaly score Remaining Useful Life (RUL)	LSTM, CNN, LSTM-autoencoder, Mahalanobis distance, KDE	Provide: Early warnings of abnormal assets under dynamic plant loads and operating shifts	Automated inspection scheduling; Targeted fan/bearing interventions; Digital twin & edge integration.	Moutsopoulou et al. [12], Hu et al. [44]

Note: WT = Wavelet Transform; FEA = Finite Element Analysis; KDE = Kernel Density Estimation; v_{RMS} = root-mean-square velocity; a = acceleration; x = displacement; f = frequency.

3.4. Passive, active, semi-active, and hybrid vibration mitigation

Vibration mitigation strategies are classified as passive, active, semi-active, and hybrid strategies [12, 13]. Passive methods include foundation stiffening, dynamic balancing, shaft alignment, resilient mounts, rubber isolation pads, spring isolators, tuned mass dampers, structural reinforcement, and damping treatments. These methods are relatively simple to implement and robust, and are suitable for reducing the transmission of steady vibration. However, they are generally tuned to a limited frequency range and may fail under other operating conditions.

Active vibration control applies counteracting forces in real time using sensors, controllers, and actuators. An example of practical actuator-based vibration control is electromagnetic excitation for ESP rapping systems. Kim et al. proposed a compact electromagnetic vibration exciter as an alternative to conventional hammer-type dry rapping for space-limited applications, such as subway-tunnel air-cleaning systems. The collecting-plate modes are identified using ANSYS modal analysis, and the dynamic response of the electromagnetic actuator is analyzed using MAXWELL simulations in their study. The excitation force is generated by the interaction between magnetic flux and the coil current, so the rapping input can be controlled by the supplied sinusoidal current and excitation frequency. This implies that smart rapping could shift from a fixed, mechanical impact to frequency-controlled excitation. However, field-scale validation is yet to be demonstrated before this type of system can be generalized to large industrial ESPs [45].

Piezoelectric actuators, electromagnetic actuators, and active mounts can be employed to attenuate certain modes of vibration when the disturbance is measurable and controllable [9, 12]. Active control is of greatest interest for application to ESP in fan assemblies, duct panels, support frames, and precision-aligned components. Active systems, however, require a power supply, control stability, reliable sensors, and protection from harsh industrial environments. Semi-active techniques, such as magnetorheological dampers and controllable-stiffness devices, are an intermediate solution. They don't apply large control forces but adapt damping or stiffness to operating conditions [13]. Hybrid systems combine passive robustness with active or semi-active adaptation. For ESPs, this means that conventional isolation and structural reinforcement can be combined with smart sensors, variable damping, adaptive rapping control, and predictive maintenance. Such hybrid strategies are more tractable than a full reliance on fully active control in dusty, hot, and electrically noisy environments.

3.5. Predictive maintenance and intelligent vibration monitoring

Smart vibration monitoring is valuable because it converts vibration data into maintenance decisions. In a perception-analysis-execution architecture, vibration sensors are part of the perception layer, FFT, wavelet transform, CNN, LSTM, autoencoder and statistical thresholding are part of the analysis layer and maintenance alerts, fan balancing, rapping adjustment, bearing replacement or shutdown scheduling are part of the execution layer. The execution layer might also comprise frequency-tuned electromagnetic excitation (actuator current and excitation frequency are tuned to the identified modal response and the desired rapping acceleration for smart rapping systems) [46].

A programmable logic controller (PLC) offers a practical execution layer path for the ESP rapping and vibration control. Zhang et al. replaced the traditional single-chip microcomputer control of the ESP vibration motors with a Schneider PLC-based system and reported improved automation, reliability, stability, and dust-removal performance under dust-emission concentrations ≤ 50 mg/m^3. The PLC communicated with a computer via RS485, transmitted field data for site monitoring, and enabled changes to internal timers and counters to keep the ESP operation close to its preferred state. The control sequence also disallowed simultaneous operation of motors in the same or adjacent electric fields, thus reducing the risk of dust re-entrainment during rapping. This example demonstrates that smart vibration mitigation requires not only sensing and diagnosis but also reliable field-level execution logic for timing, sequencing, interlocking and feedback-based adjustment [47].

This structure links vibration mitigation directly with operational decision-making. Predictive maintenance is especially critical as ESP-related vibration faults tend to develop over time. Vibration signatures from bearing defects, fan imbalance, loose supports, and rapping-system wear can be detected prior to catastrophic failure. A smart monitoring platform can compare current vibration features to baseline behavior, identify deviations, and estimate the remaining useful life of critical components. Statistical procedures such as moving thresholds, kernel density estimation, Mahalanobis distance, and residual analysis can reduce false alarms by adapting to changing load conditions [44]. In addition to electrical and emission data, vibration monitoring can help determine whether outlet concentration peaks are caused by electrical instability, rapping disturbance, airflow fluctuations, or mechanical degradation.

Despite these operational advantages, several important technical deficiencies remain unaddressed. A major limitation is that most vibration control studies are not specifically tailored to ESP architectures, so there is remarkably little direct field evidence on vibration reduction in ESP fans, rapping systems, or electrode assemblies. Additionally, there are no standardized vibration metrics for ESP components yet. Future investigations to address this inconsistency will need to systematically report the root-mean-square vibration velocity (mm/s), acceleration (m/s^2), displacement (μm), and dominant frequency (Hz) with corresponding operating loads, accurate sensor locations, and long-term maintenance results. Further, vibration mitigation strategies need to be evaluated in terms of dust collection efficiency, energy consumption, and noise generation. A localized strategy that mitigates vibration at the cost of increased pressure drop, increased acoustic emission, or increased maintenance complexity is not optimal at the system level. Thus, future ESP research should evolve from the isolation of component-level vibration reduction to integrated, multi-sensor, multi-objective, and field-validated smart monitoring systems.

4. Noise reduction in electrostatic precipitators

In electrostatic precipitator systems, noise is generated from the collective operation of fans, ducts, motors, transformer-rectifier units, gas-flow passages, rapping mechanisms, and structural vibration [25–27, 48]. Unlike electrical efficiency, which is typically quantified using energy and emission indicators, noise reduction must be characterized in terms of the sound source, transmission path, receiver exposure, and frequency content. ESP-related noise is therefore not just an occupational comfort issue but also an operational indicator of fan condition, airflow instability, rapping impact, structural looseness, and equipment deterioration. Smart noise reduction should incorporate acoustic monitoring, vibration diagnosis, passive attenuation, and active control, rather than relying solely on enclosure-based treatment.

4.1. Noise-generation mechanisms in ESP systems

The main sources of acoustic emissions in ESP installations can be classified as aerodynamic, mechanical, electrical, and impact sources. Induced-draft fans, turbulent flow, sudden duct expansion or contraction, vortex shedding, dampers, bends, and gas-flow maldistribution are the sources of aerodynamic noise. Fan noise normally has broadband contributions from turbulence and tonal contributions at the blade-passing frequency and its rotational harmonics. Motors, bearings, gearboxes, couplings, and structural vibration are sources of mechanical noise transmitted through ducts, frames, casing walls, platforms, and foundations. Sources of electrical noise include transformer-rectifier units, high-voltage power supplies, cooling fans, corona discharge, sparking, and electrical cabinet vibration. Impact noise is mainly associated with rapping systems, where hammering or electromagnetic impacts are used to remove dust from collecting plates and discharge electrodes [25, 48].

These noise mechanisms are strongly coupled with vibration and process operation.

For example, fan imbalance can increase vibration and low-frequency sound pressure; rapping intensity can improve dust cleaning but generate transient impulsive noise; and airflow maldistribution can increase pressure loss, turbulence, and acoustic radiation. The ESP noise should therefore be assessed using the overall A-weighted sound pressure level (dB(A)) and frequency-resolved indicators, such as octave-band or one-third-octave-band spectra. A single dB(A) value is useful for compliance assessment, but frequency spectra are required to select appropriate control measures, as low-frequency fan noise, mid-frequency duct resonance, and high-frequency electrical or impact noise require different mitigation strategies.

4.2. Passive noise-control strategies: Source and transmission-path treatment

The first practical layer of ESP acoustic mitigation is passive noise control. At the source level, fan selection, blade design, rotational speed control, motor maintenance, bearing alignment, and aerodynamic smoothing can reduce noise generation before it propagates through the system. At the transmission-path level, acoustic enclosures, silencers, duct lining, expansion chambers, flexible connectors, absorptive barriers, and vibration isolators can reduce the radiation and transmission of sound from fans, ducts, motors, and transformer-rectifier rooms [25–27,48]. For rapping systems, impact noise can be reduced by optimizing the hammer force, rapper timing, electrode support stiffness, and dust-removal frequency to preserve cleaning efficiency without excessive structural excitation.

The effectiveness of passive treatment is highly frequency dependent. Porous absorbers and duct linings are most effective at middle and high frequencies, whereas attenuating fan noise at low frequencies is more difficult, as it requires larger silencers, tuned resonators, heavier barriers or active control. Acoustic-flow-path design can also assist passive mitigation. In research on façade-integrated ESP filtration, a U-shaped flow channel and a sound-absorbing section are proposed to avoid direct sound transmission while maintaining low pressure loss and particle filtration capacity [49]. The application is not the same as large industrial ESPs, but the design principle is applicable. Acoustic attenuation should be combined with airflow management to ensure that noise reduction does not impose a significant pressure drop or increase energy consumption.

4.3. Active noise control and adaptive algorithms

Active noise control (ANC) is most effective for low-frequency tonal or broadband noise, where passive silencers become bulky or ineffective. A typical feedforward ANC system is composed of a reference microphone to detect the primary noise, an adaptive controller to generate an antiphase control signal, a secondary loudspeaker to produce the control signal, and an error microphone to sense the residual sound field. The controller iteratively adapts the filter so that the secondary sound destructively interferes with the primary noise at the desired location [14].

The filtered-X least mean square (FxLMS) algorithm is commonly used in active noise control because it accounts for the secondary acoustic path between the control loudspeaker and the error microphone. Without this correction, the adaptive filter may converge slowly or become unstable as the emitted anti-noise may be modified by the loudspeaker, duct, reflection field, and microphone path before reaching the error sensor. More advanced algorithms, including filtered-X affine projection (FXAP), filtered-X quasi-affine projection (FXQAP), variable-step-size FXQAP, and distributed ANC algorithms, enhance convergence and robustness when reference signals are colored, non-stationary, or subject to complex acoustic paths [14]. These features are relevant for ESP auxiliary systems, as fan and duct noise often have periodic, broadband, and flow-modulated components. Hybrid passive-active systems seem to be the most promising, as passive silencers and ANC work in different frequency ranges. In a ventilation-duct experiment, the performance of a passive silencer was greater than 20 dB attenuation for frequencies above 600 Hz, while in the same experiment, the performance of a feedforward ANC system was greater than 10 dB attenuation between 70 and 200 Hz, with a maximum attenuation of about 17 dB at around 150 Hz for duct wind speeds of 5–10 m/s [31]. While this evidence is obtained from ventilation ducts rather than industrial ESPs, it is directly relevant to ESP fan and duct noise control because both systems involve confined airflow, duct propagation, and low-frequency fan-related acoustic components. In practice, feedforward ANC implementation in such high noise environments aims for a large reduction of low-frequency tonal peaks, typically resulting in a reduction of overall noise levels in the vicinity of the fan from an occupational hazard level of over 90 dB(A) to a safer compliance level below 80 dB(A) [25]. Thus, the new ESP noise control strategy should include passive silencers for high-frequency attenuation and active noise control for low-frequency fan and duct noise.

4.4. IoT-based acoustic monitoring and noise mapping

Smart ESP noise reduction is based on continuous acoustic monitoring. IoT-based sound monitoring systems can collect dB(A), timestamp, location, and frequency-related information from distributed sensor nodes and transmit the data to a local gateway, cloud database, or dashboard for visualization and analysis. A low-cost IoT noise monitoring system using ESP8266/Arduino hardware, sound sensors, MySQL storage, and real-time dashboards proved that calibrated sensor networks can provide continuous spatial and temporal noise information [27]. Such architectures can be applied to ESP plants by placing acoustic sensors near fans, motors, rapping systems, transformer-rectifier units, duct bends, and worker access areas.

The main benefit of IoT-based acoustic monitoring is that it shifts noise control from sparse manual measurements to continuous condition assessment. Time histories can detect abnormal peaks in sound during rapping, changes in the spectrum due to fan wear, and increasing noise trends due to bearing faults or airflow blockage. Acoustic monitoring, particularly when augmented by vibration and electrical data, can help distinguish whether a noise event is due to mechanical degradation, rapping impact, spark activity, or gas-flow disturbance. Noise maps can also identify high-exposure areas and guide the placement of barriers, silencers, enclosures, or active control devices. The monitoring platform shall record A-weighted sound pressure level, equivalent continuous level, peak level, dominant frequency, operating load, and equipment state for regulatory and occupational assessment.

4.5. Hybrid noise-reduction strategies and implementation constraints

The most effective noise reduction strategy for smart ESPs is a hybrid source-path-receiver approach. The source control should focus on fan selection, speed optimization, bearing maintenance, rapping-force adjustment, and vibration of the power supply cabinet. Path control should include duct silencers, flexible joints, absorptive linings, vibration isolation, and acoustic enclosures. Receiver protection should be designed with worker zone noise mapping, barriers, warning thresholds, and maintenance planning. When passive treatment is still not enough to dominate low-frequency fan or duct noise, active control should be employed.

There are, however, several constraints for industrial implementation. If not designed with the airflow requirements in mind, acoustic devices may increase the pressure drop. ANC performance is a function of the microphone and loudspeaker placement, secondary-path modeling, time delay, robustness to airflow noise, and the protection of sensors from dust, temperature, and electromagnetic interference. Transient noise from rapping and sparking may not be adequately controlled by steady-state ANC algorithms. Most published ANC and IoT noise-monitoring studies are not specific to ESPs; therefore, direct field validation in ESP installations remains lacking. Therefore, future studies should report the pre- and post-sound pressure levels in dB(A), one-third-octave-band spectra, operating load, airflow rate, fan speed, sensor locations, and control settings.

Overall, ESP noise reduction is moving from passive enclosure design toward data-driven acoustic management. The most promising direction is not a single technology but the integration of passive attenuation, active low-frequency control, IoT-based noise monitoring, vibration diagnosis, and airflow-aware design. Such integration can reduce worker exposure, improve acoustic comfort, and provide an additional diagnostic signal for equipment health and process stability.

5. Integration of smart technologies in ESPs

Smart electrostatic precipitators should not be seen as conventional ESPs with isolated sensors or add-on artificial intelligence. They are useful for the integrated coordination of electrical control, vibration diagnostics, acoustic monitoring, rapping optimization, fan operation, emission compliance, and maintenance decision-making. Previous sections have shown that smart technologies can improve electrical efficiency, vibration mitigation, and noise reduction, but these subsystems interact strongly in real operation. For example, lowering the voltage may reduce energy use, but may also reduce dust collection [34]. Rapping may restore electrode cleanliness but may also cause increased vibration and impulsive noise. Fan-speed control may reduce energy consumption but change pressure drop, residence time, and acoustic behavior. Therefore, the main challenge for smart ESP development is system-level collaborative optimization instead of isolated subsystem improvement [34, 50–53].

5.1. Perception-analysis-execution architecture

We propose a three-layer architecture: perception-analysis-execution as a framework to classify smart ESPs. The perception layer collects real-time information from electrical, particulate, mechanical, acoustic, and process sensors. The analysis layer processes these data into operational intelligence through signal processing, machine learning, digital twins, statistical diagnosis, and optimization algorithms. The execution layer then converts the analytical results into actions, namely voltage/current adjustment, rapping control, fan-speed regulation, vibration suppression, active noise control, and maintenance scheduling.

The proposed perception-analysis-execution structure is summarized in **Figure 4**. The operation of smart ESP is organized into multi-source sensing, AI-supported analysis, and coordinated execution. It explicitly integrates electrical optimization, vibratory diagnosis, acoustic control, rapping adjustment, fan operation and maintenance scheduling in a single closed-loop framework [6, 7, 14, 44]. Perception Layer collects electrical, emission, process, vibration, acoustic and maintenance data. Analysis Layer applies signal processing, AI, digital twins and multi-objective optimization, and Execution Layer performs adaptive voltage control, rapping optimization, fan speed adjustment, vibration mitigation, active noise control and maintenance scheduling. The closed feedback loop allows for cooperative optimization of electrical, mechanical, acoustic and operational subsystems [6,7,14,44].

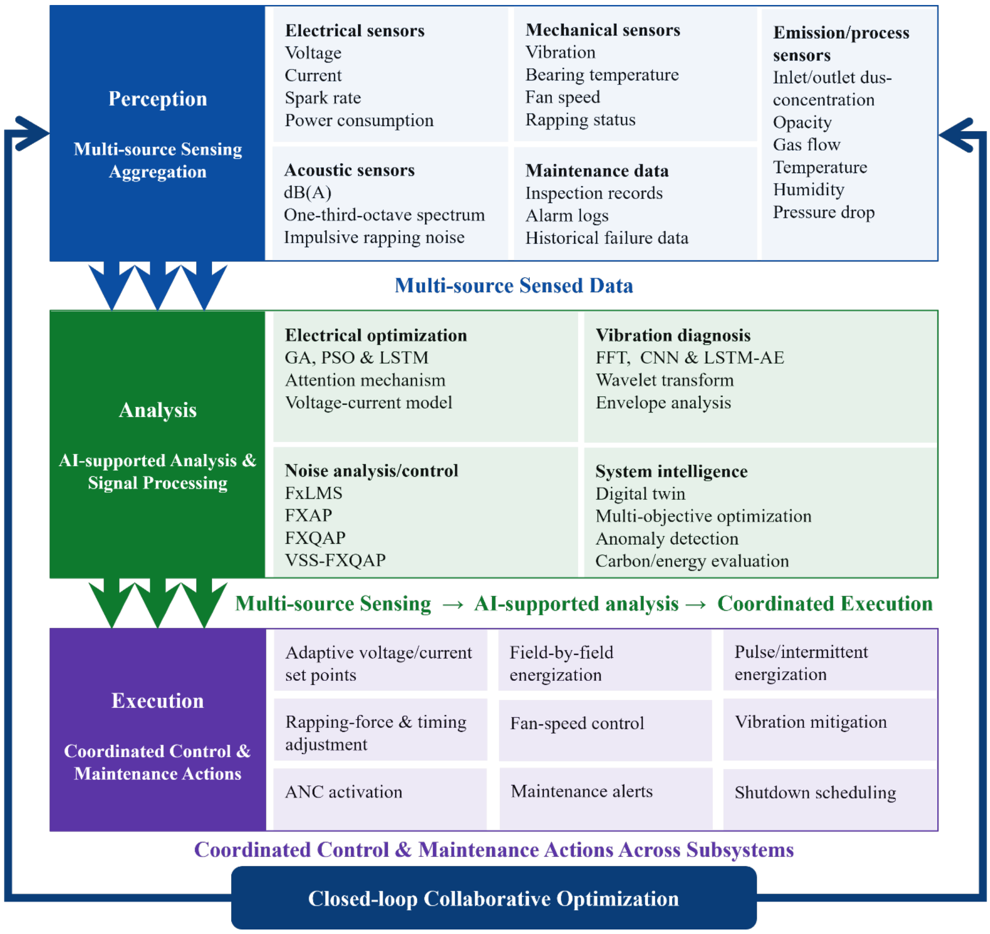

Figure 4. Perception–analysis–execution architecture for smart ESPs embedded in systems.

This architecture is a direct answer to the need for a clearer theoretical framework in smart ESP research. Control choices in traditional ESP operation are often based on operator expertise, static regulations, or limited input like secondary voltage/current and outlet opacity. In a smart ESP, these measurements are part of a larger cyber-physical loop in which the system continuously monitors plant conditions, predicts performance, identifies the best actions, and updates control settings. This principle has been demonstrated by real-time intelligent optimisation systems that link outlet concentration prediction, optimisation, coordination, monitoring, and power-supply execution. This principle has already been demonstrated by real-time intelligent optimisation systems, which consist of five layers: optimisation, coordination, monitoring, communication, and execution. The industrial ESP studied by Zheng et al. was equipped with a closed-loop control platform comprising IOS-connected outlet-concentration prediction, PSO-based voltage optimisation, rapping-tolerant coordination logic, CEMS/PLC/OPC communication, and power-supply execution [6]. Deep-learning-assisted ESP control is another illustration of how physical voltage-current modeling, long short-term memory prediction, attention mechanisms, and particle swarm optimization can be combined to pick energy-saving voltage settings under dynamic power-plant conditions [7]. These examples show that the future of ESP control lies in closed-loop integration, not in smart devices alone.

5.2. Multi-source sensing and data integration

The perception layer of a smart ESP needs to collect synchronized multi-source data [50–52]. Electrical sensing includes primary and secondary voltages, current, spark rate, corona power, pulse frequency, rapping status, and transformer-rectifier operating conditions. Emission and process sensing includes inlet and outlet dust concentration, opacity, gas flow, temperature, pressure drop, humidity, oxygen content, boiler load, and fuel or raw-material variation [34, 53, 54]. Mechanical sensing includes vibration signals from induced-draft fans, motors, bearings, gearboxes, rapping systems, support frames, and duct structures [55]. Acoustic sensing is used to measure dB(A), peak sound pressure, octave-band or one-third-octave band spectra, and impulsive events near fans, ducts, rapping devices, transformer-rectifier units, and worker-access areas [14,15,27].

The main difficulty is not just the installation of the sensors, but the fusion of heterogeneous data streams with different sampling rates, physical meanings, and reliability levels [56]. Dust concentration sensors can be subject to delays and drift. Voltage and current can be recorded with high temporal resolution. Vibration sensors give high-frequency mechanical information. Acoustic sensors are sensitive to background noise and spatial reflection. Process signals, such as temperature, humidity, and gas flow changes, are slower but have strong effects on dust resistivity, corona behavior, collection efficiency, and pressure drop. Therefore, before the higher-level analysis can be reliable, a smart ESP platform must provide data synchronization, filtering, calibration, feature extraction, fault screening, and secure storage.

Cross-validation of faults is also possible with multi-source sensing. A sudden outlet dust peak can be caused by voltage instability, rapping disturbance, fan-speed change, electrode misalignment, gas-flow maldistribution, or sensor error. Electrical data alone may not differentiate these mechanisms. However, if there is an increase in outlet concentration with rapping impact, casing vibration, and acoustic impulse, the event may be rapping-related. Mechanical degradation or airflow instability could be suggested by increased vibration and low-frequency noise near the fan as gas flow fluctuates. This cross-domain interpretation is one of the major benefits of smart ESP integration.

5.3. Collaborative optimization and execution control

The analysis layer should be able to transform multi-source data into optimized decisions. GA, PSO, neural networks, LSTM models, attention mechanisms, and hybrid physical-data models can be used to predict outlet dust concentration and minimize power consumption under emission constraints to improve electrical efficiency [6,7,33]. Vibration mitigation: They can identify imbalances, misalignments, resonances, bearing defects, and abnormal fan behavior. FFT, wavelet transform, envelope analysis, convolutional CNNs, LSTM models, and autoencoders [9,11–13,44]. Active control of low-frequency fan and duct noise supported by algorithms such as FxLMS, FXAP, FXQAP, and variable-step-size FXQAP can achieve noise reduction [15].

The execution layer should orchestrate these results, not implement them in a vacuum. Field-level voltage optimization can contribute to the reduction of corona power, but it has to be compatible with rapping schedules, spark stability, and outlet concentration targets [7]. Rapping control should take into account dust layer thickness and collection performance, but also avoid excessive structural vibration and impulsive noise. Outlet-field rapping can produce sharp disturbances in PM concentration, so rapping control should be coordinated with emission feedback. In the industrial ESP data of Zheng et al., field plate rapping had the greatest impact on the outlet PM concentration, and plate rapping at this outlet field resulted in a concentration disturbance lasting more than 200 s. Accordingly, rapping schedules should be coordinated with voltage control and emission averaging, rather than being considered as fixed mechanical cleaning events [6]. Fan-speed optimization should consider pressure drop and energy consumption, but must preserve gas residence time and prevent flow-induced vibration

Fan operation, pressure drop, residence time and velocity distribution should be optimized, because a non-uniform gas flow can reduce the effective use of collecting surfaces even if the electric field is sufficient. CFD-experimental evidence from a compact tubular ESP showed that a 50 mm partially inserted flow straightener delivered the most balanced velocity distribution and the highest collection efficiency, while full insertion increased pressure drop and reduced performance, confirming that aerodynamic execution must be coordinated with electrical control [57].

Airflow optimization should consider pressure drop, residence time, and velocity distribution, as non-uniform flow can reduce the effective use of ESP collecting surfaces. The compact tubular ESP with a 50 mm partially inserted flow straightener yielded the most balanced velocity distribution and the highest collection efficiency, whereas full insertion increased pressure drop and reduced performance [57, 58]. **Figure 5** shows the corresponding CFD velocity-field comparison for the three flow-straightener configurations. Active noise control may reduce low-frequency sound, but microphone and loudspeaker placement must be robust to dust, airflow turbulence, and electromagnetic interference [59]. These examples show that single-objective control is insufficient. Case A represents the baseline without a flow straightener, Case B represents 50 mm partial flow-straightener insertion, and Case C represents 100 mm full insertion. The 50 mm configuration produced the most balanced velocity distribution across the tubular ESP components and corresponded to the highest measured collection efficiency of 93.09%, indicating that airflow uniformity and pressure-drop management are important variables in collaborative ESP optimization.

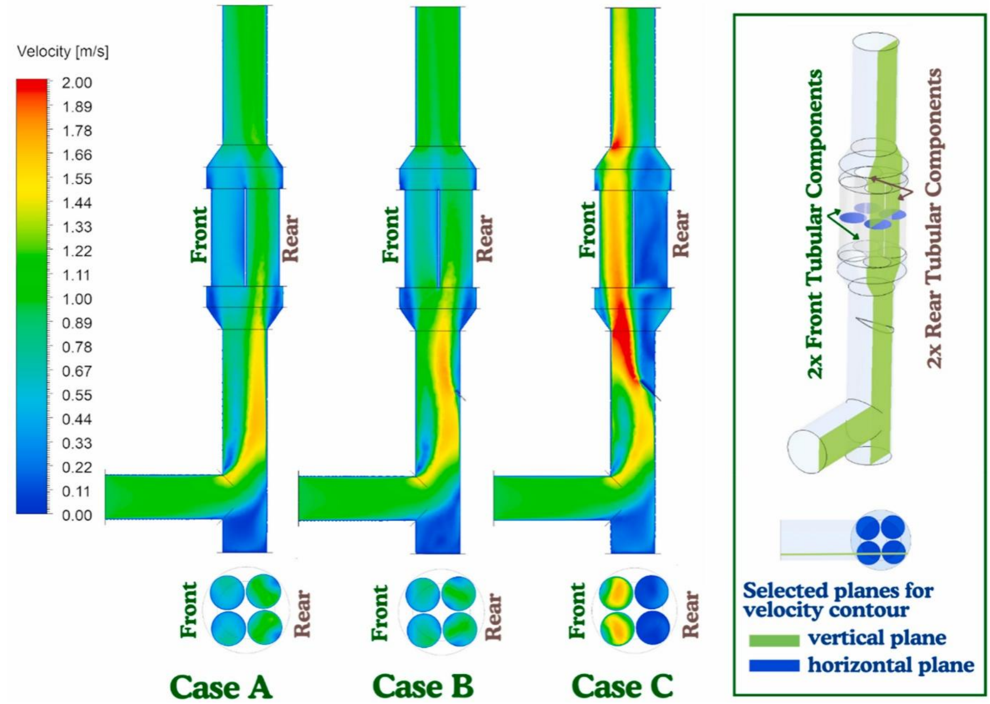

Figure 5. CFD velocity-field comparison of ESP airflow optimization using different flow-straightener configurations.
Source: Reproduced from Kantová et al. [57].

Multi-objective collaborative optimization is a more appropriate approach. The objective function should include emissions compliance, energy consumption, spark rate, voltage stability, vibration amplitude, noise level, ozone formation, pressure drop, maintenance cost, equipment life, and carbon reduction [31,58]. These objectives may be given different weights depending on operational priorities. For example, emission stability may be favored during high-load operation, energy saving during stable low-load operation, and vibration and bearing condition during maintenance-sensitive periods [6]. Such adaptive weighting is central to practical smart ESP control [7].

5.4. Industrial demonstrations and case-based evidence

Several studies indicate that smart or optimized ESP operation can deliver measurable benefits, but real-world multi-technology collaborative optimization cases remain scarce. A real-time intelligent optimization system for an industrial ESP under ultra-low-emission operation improved compliance from 95% to 100%, moved the median outlet concentration 46.6% closer to the target, and achieved 35.50% energy conservation under an emission upper limit of 30 mg/m^3 [6]. The importance of this case is that the energy savings were not just from voltage reduction, but from an integrated system that predicted outlet concentration, optimized field voltage set points at the field level, compensated for rapping-induced emission variations, and implemented the corrected voltages through the plant control infrastructure.

The optimization study of a 330 MW coal-fired power plant ESP, assisted by deep learning, combines a voltage-current mechanism model, LSTM prediction, an attention mechanism, and PSO. The voltage-current model achieved a mean absolute percentage error of 1.43%, the outlet concentration model achieved a testing-set MAPE of 5.2%, and the optimization experiment achieved about 43% energy savings with an estimated annual carbon reduction of 2,621.34 t over 300 operating days [7].

Also, previous optimization studies have supported the benefit of field-level collaborative control. A factual multi-field ESP based on a radial-basis-function neural-network modeling and voltage-power fitting using a GA-based strategy to optimize the secondary voltage distribution. The application reported a reduction in the total power in the order of 16 kVA, 8 kVA, and 18 kVA at outlet concentration limits of 50, 40, and 30 mg/Nm^3, respectively [31]. Decreased SPM levels relative to the conventional control were also observed with adaptive feed-forward ESP control using opacity or solid particulate matter feedback. Typical 1:1 pulse-rate values dropped from an average of 45–49 mg/m^3 to an average of 20.5–29.1 mg/m^3 [37].

Other cases are best regarded as corroborative rather than full-blown demonstrations of smart ESP. Electrical characterization at Thermal Power Plant Mantia, Deva, Romania, proved the importance of real current-voltage behavior and electrode-field simulation for the automation readiness [33]. LSTM-autoencoder anomaly detection for induced-draft fan equipment in a power plant demonstrated the relevance of early warning based on deep learning for auxiliary rotating machinery associated with ESP operation [44]. The cement-plant dust-emission monitoring in central-north Romania in 2018–2020 is a useful piece of evidence of industrial emissions, but it should be treated as an industrial monitoring case, not as a direct smart ESP optimization case [60].

Flow-conditioning optimization is another enabling case for system-level ESP improvement. Kantová et al. conducted CFD simulations and experimental measurements for a tubular ESP downstream of an 18-kW pellet boiler. The original single-tube ESP was changed to a compact four-tube arrangement, and three upstream flow-straightener configurations were compared. The best performance was obtained for 50 mm partial insertion, with a collection efficiency of 93.09% and a normalized PM concentration of 30.70 mg m^{-3} with the ESP off and 2.12 mg m^{-3} with the ESP on. The same case also maintained a low-pressure drop of 1.28 Pa, similar to the no-straightener case, whereas full insertion increased the pressure drop to 2.25 Pa and reduced efficiency. These results support the notion that the control of airflow distribution and pressure drop should be treated as part of collaborative ESP optimization, rather than as secondary duct design details [57].

Taken together, these studies show that smart ESP development is advancing, but the literature is still lacking field studies that simultaneously optimize electrical energy, vibration, noise, rapping, fan operation, and maintenance. These studies show that smart ESPs are emerging, but few field studies in the literature simultaneously optimize electrical energy, vibration, noise, rapping, fan operation, and maintenance.

5.5. Technology readiness, barriers, and opportunities

Smart ESP functions are at very different technology readiness levels. High-voltage power control, spark control, opacity feedback, field-level energization, and conventional vibration monitoring are relatively mature. Adaptive topologies, such as high-frequency power supplies that dynamically adjust the pulse repetition rate to account for space charge buildup and nonlinear corona discharges, have shown energy savings of 12–18% while improving submicron particle collection efficiency by 8–15% [61].

IoT-based acoustic monitoring, predictive maintenance, GA/PSO voltage optimization, and LSTM-based emission prediction are at an intermediate stage, as they have been demonstrated in relevant industrial or laboratory contexts but still require wider plant-scale validation [62–65]. Recently, hybrid empirical-numerical models combining electrostatics, laminar flow, and particle tracing have delivered high-fidelity baseline validations (e.g., Mean Absolute Error of ~5.3%) and provide fast alternative methods to computationally expensive full-scale CFD simulations for design optimization [66]. Similarly, coupled corona-discharge, flow-field, and particle-transport simulations of folded collecting plates demonstrate the possibility of utilizing numerical design tools to pre-screen electrode/plate geometries prior to industrial retrofitting, although such geometry-specific results must still be validated with more general experiments and in the field [67]. However, translating these localized models into real-time industrial contexts remains an ongoing hurdle.

But translating these localized models to real-time industrial settings remains a challenge. Digital twins, edge-cloud collaborative control, distributed active noise control, and integrated multi-objective ESP optimization are still less mature [7, 14, 44, 68, 69] and should be considered as emerging research directions [70]. In the wider scope of environmental engineering, the incorporation of digital tools like digital twins and IoT-based predictive modeling is gaining ground as crucial for enhancing system scalability, operational reliability, and real-time carbon capture or emission frameworks [71].

There are several critical barriers that must be addressed to enable the broad deployment of smart ESPs. A major issue is that industrial ESP datasets are mostly site-specific, proprietary, incomplete, or corrupted by sensor drift and maintenance breaks; these drawbacks severely restrict the transferability of models across different plants, fuels, dust types, and operating regimes. Furthermore, hardware resilience is a major challenge, as sensors and controllers must withstand harsh ESP environments, including high voltage, heavy dust deposition, vibration, humidity, extreme temperature fluctuations, and electromagnetic interference. In addition, current AI research primarily focuses on prediction accuracy or energy optimization, largely ignoring long-term reliability, false-alarm rates, maintenance outcomes, and overall cost-benefit performance. Finally, critical operational integration remains under-researched, with the literature rarely addressing cybersecurity protocols or interoperability with plant distributed control systems, supervisory control and data acquisition systems, and continuous environmental monitoring frameworks.

Future research, therefore, may transcend these barriers by moving to a number of interconnected paradigms. Smart ESP literature should standardize documentation of key parameters, including gas flow, inlet and outlet dust concentrations, voltage and current ranges, field numbers, spark rates, vibration amplitudes, noise levels, energy consumption, and operating loads. The data standardization should be complemented with the development of multi-objective optimization frameworks to efficiently trade off competing objectives such as emission compliance, energy consumption, mechanical vibration, noise generation, ozone formation, pressure drops, and lifecycle maintenance costs. The combination of digital twins and physics-informed machine learning provides a promising pathway to enhance algorithmic interpretability and cross-plant transferability, thereby bridging the gap in model generalization [7]. Ultimately, support for low-latency localized control and long-term, fleet-level collective learning will require deploying edge computing, next-generation mobile communications (5G/6G), secure industrial IoT architectures, and cloud-based analytics. The implementation of these advances will enable smart ESPs to comply with stringent environmental standards while being cost-effective.

6. Conclusion

The smart electrostatic precipitators should be evaluated by the integrated indicators of emission compliance, energy consumption, vibration stability, acoustic performance, maintenance reliability, and carbon reduction. The proposed perception-analysis-execution framework provides a solid foundation to connect multi-source sensing, signal processing, artificial intelligence, and coordinated control actions.

The strongest quantitative evidence is for electrical optimization. Reported ESP energy consumption can be below 0.3 Wh/m^3 in some applications. Real-time intelligent optimization reduced ESP energy consumption by 35.50% while improving emission compliance from 95% to 100% under an outlet concentration limit of 30 mg/m^3. In a 330 MW coal-fired power-plant ESP, LSTM-, attention-, and PSO-based voltage optimization achieved approximately 43% energy saving and an estimated annual carbon reduction of about 2,621.34 t over 300 operating days. They confirm that adaptive voltage/current control and AI-assisted prediction can improve efficiency without sacrificing emission stability.

The review emphasises the importance of additional quantitative field validation for vibration and noise control. FFT, wavelet transform, envelope analysis, RMS tracking, CNNs, LSTM models, and autoencoders can support vibration diagnosis and predictive maintenance. Hybrid passive-active noise control has achieved more than 10 dB attenuation in the 70–200 Hz range and more than 20 dB passive attenuation above 600 Hz in duct systems relevant to ESP auxiliary equipment. However, ESP-specific before-after datasets for vibration and noise reduction remain limited.

Future research directions should focus on digital twins, edge computing, communication based on 5G/6G, secure industrial IoT, and multi-objective optimisation. Long-term demonstrations in power plants, cement plants, steel plants and waste-treatment plants are necessary to optimise dust emissions jointly, energy consumption, spark stability, rapping behaviour, vibration amplitude, noise level, ozone formation, pressure drop, equipment life and maintenance cost.

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