INNOVATIVE SENSOR-BASED PREDICTIVE SYSTEM FOR EMISSION FORECASTING AT WASTE-TO-ENERGY FACILITIES

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Abstract. *The accelerating expansion of Waste-to-Energy (WtE) infrastructure across Central Asia has intensified the need for real-time analytical tools capable of interpreting complex emission dynamics. The development of WtE facilities is accompanied by high variability and transient peaks in pollutant emissions, posing new challenges for environmental and occupational safety. Traditional laboratory-based and static monitoring methods lack sufficient temporal resolution to detect these transient emissions. This study proposes an intelligent sensor-based predictive emission monitoring system, integrating distributed multi-sensor networks, stochastic emission modeling, Kalman-based signal filtering, and short-horizon neural network forecasting. The system enables early detection of potentially hazardous states, provides a scientifically grounded framework for integrated environmental and occupational risk assessment, and serves as a foundation for digitalized environmental control processes within the context of Uzbekistan's sustainable development and green economy strategy.*

Keywords: *Waste-to-Energy; sensor networks; predictive emissions modeling; digital environmental monitoring; stochastic modeling; Kalman filtering; recurrent neural networks; environmental risk; occupational safety; sustainable development; green economy.*

ИННОВАЦИОННАЯ СЕНСОРНАЯ СИСТЕМА ПРОГНОЗНОЙ ОЦЕНКИ ВЫБРОСОВ НА ОБЪЕКТАХ WASTE-TO-ENERGY

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Аннотация: *ускоренное развитие объектов переработки отходов в энергию (Waste-to-Energy, WtE) в Центральной Азии усиливает необходимость интеллектуальных инструментов для анализа выбросов в реальном времени, способных интерпретировать сложную динамику загрязнений. Развитие WtE сопровождается высокой вариабельностью выбросов и кратковременными пиками загрязняющих веществ, что создаёт новые вызовы для экологической и производственной безопасности. Традиционные лабораторные методы и стационарные посты мониторинга не обеспечивают достаточной временной разрешающей способности для выявления переходных выбросов. В работе предложена интеллектуальная сенсорная система прогнозной оценки выбросов, основанная на распределённой многосенсорной архитектуре, стохастическом моделировании, фильтрации сигналов методом Калмана и краткосрочном прогнозировании с применением рекуррентных нейронных сетей. Система обеспечивает раннее выявление потенциально опасных состояний, формирует научно обоснованный механизм интегральной оценки экологических и производственных рисков, а также служит основой для цифровизации процессов экологического контроля в рамках стратегии устойчивого развития и зелёной экономики Узбекистана.*

Ключевые слова: *Waste-to-Energy; сенсорные системы; прогнозирование выбросов; цифровизация; стохастическое моделирование; фильтр Калмана; рекуррентные нейронные сети; экологические риски; производственная безопасность; устойчивое развитие; зелёная экономика.*

Introduction.

As Waste-to-Energy technologies advance, their operation is increasingly characterized by rapid temperature fluctuations, unstable feed composition, and variable combustion regimes, each contributing to highly dynamic emission behavior. Transient peaks of PM2.5, CO, NO_2 , VOCs, and other pollutants—often lasting only seconds—are insufficiently captured by conventional monitoring infrastructures, which remain optimized for periodic sampling rather than continuous environmental assessment [1]. In regions undergoing active WtE development, such as Uzbekistan, this monitoring gap creates elevated occupational risks and limits the capacity of regulatory bodies to enforce timely environmental interventions.

Predictive analytics, grounded in continuous sensor-based observations, offers a pathway toward anticipatory environmental management. Unlike retrospective laboratory analyses, predictive monitoring enables the system to register deviations in near real time, identify precursors of emission surges, and support informed operational decisions. The goal of the present study is to elaborate a scientifically consistent methodological basis for such a system, integrating hardware, stochastic modeling, and machine-learning components into a cohesive technological solution.

Scientific Rationale and Problem Context.

The emission profile of WtE facilities is distinguished by pronounced nonlinearity originating from the intrinsic heterogeneity of municipal solid waste and the micro-scale variations in combustion chamber conditions. The interaction of fuel composition, temperature gradients, oxygen availability, and turbulence produces pollutant fluctuations that cannot be approximated by steady-state or mean-value models [2]. Importantly, many of the most hazardous spikes occur during feeding cycles, incomplete combustion phases, or localized cooling and reheating events—periods in which conventional monitoring stations lack temporal resolution.

A modern predictive system must therefore treat emission concentrations as time-dependent stochastic variables rather than static measurements. This shift toward dynamic modeling acknowledges the intermittent, burst-like nature of pollutant formation and allows integration of transient features into forecasting pipelines. More broadly, it aligns with the international trend toward digital environmental management, enabling decision-makers to detect deteriorating conditions before they escalate into regulatory violations or safety hazards.

Architecture of the Multi-Sensor Node.

The sensing node constitutes the technological foundation of the predictive system. It aggregates multiple measurement modalities—optical particulate sensors, electrochemical detectors for CO and NO_2, metal-oxide VOC modules, and thermodynamic sensors—into a unified data acquisition platform [3]. The ESP32 microcontroller handles onboard preprocessing, including noise suppression, timestamp synchronization, and encrypted transmission via Wi-Fi or GSM. This architecture supports high-frequency, multi-parameter sampling, ensuring that correlations between thermal instability and pollutant release can be accurately reconstructed. The electrical schematic (Figure 1) presents the interconnections between sensor elements, power conditioning modules, and communication interfaces, illustrating the logic of distributed monitoring within industrial environments. Such a modular hardware configuration is essential for scaling the system across facility zones, providing spatial granularity that centralized measurement stations are unable to achieve.

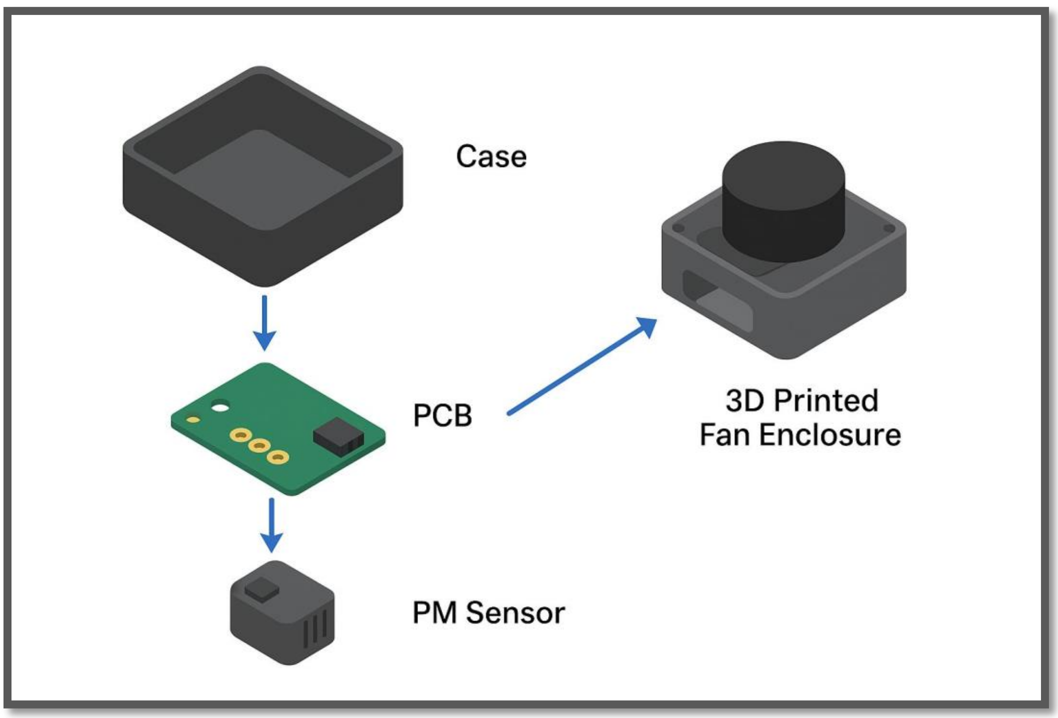

Figure 1. Electrical and structural schematic of the multi-sensor emission-monitoring node. The diagram illustrates the interconnections among particulate sensors (PM2.5/PM10), electrochemical gas modules (CO, NO_2), VOC sensors, thermodynamic instruments, power regulation circuits, and the ESP32 microcontroller, as well as their placement within the 3D-printed fan-assisted enclosure to support continuous, high-frequency, real-time monitoring

Mathematical Framework for Modeling Emission Dynamics.

A rigorous analytical framework is required to interpret raw sensor signals and convert them into predictive insights. The emission concentration *C(t)* is modeled using a stochastic differential equation that captures nonlinear responses to operational factors and environmental disturbances:

$$dC(t) = f(C(t), u(t), \theta)dt + \sigma(C(t))dW(t),$$

This formulation allows the system to represent both sudden pollutant surges and gradual concentration drifts characteristic of WtE combustion cycles.

To counteract sensor noise and measurement uncertainty, a Kalman-based filtering procedure is applied:

$$\hat{C}k|k\text{-}1 = A\hat{C}k\text{-}1|k\text{-}1 + Bu_k,$$
$$K_k = P_{k|k-1}H^T(HP_{k|k-1}H^T + R)^{-1},$$
$$\hat{C}k|k = \hat{C}k|k - 1 + K_k(z_k - H\hat{C}_{k|k-1}),$$

This filter constructs a statistically optimal estimate of the true concentration state $\hat{C}(t)$, providing a reliable basis for forecasting.

Short-term predictive modeling is conducted using a recurrent neural network with LSTM architecture:

$$h_t = LSTM(C_{t-1}, h_{t-1}), \qquad \hat{C}_{t+k} = g(h_t)$$

This hybrid structure—combining physically interpretable stochastic modeling with data-driven temporal learning—supports accurate anticipation of emerging hazardous conditions [4][5].

Predictive Risk Assessment. To translate concentration forecasts into operationally meaningful insights, the system incorporates a composite risk index:

Here *A(t)* represents the anomaly score derived from an autoencoder-based reconstruction error, while the weights w_i reflect normative and occupational priorities. Unlike threshold-based methods, this risk function captures the interaction between pollutants, thermal instability, and anomalous behavior, offering nuanced situational awareness aligned with international environmental safety standards.

By integrating continuous sensing, stochastic modeling, and machine-learning forecasting, the proposed system introduces a conceptually new paradigm in WtE emission management. Rather than reacting to measured exceedances, operators gain the capacity to anticipate hazardous states, optimize combustion conditions, and adjust ventilation or filtration mechanisms before pollutant concentrations approach regulatory limits.

Compared with the earlier conceptual sensor-monitoring framework developed in prior work, the present study advances the research by:

– introducing a unified probabilistic-forecasting engine;
– expanding sensor fusion techniques;
– formalizing a risk-oriented methodology rather than relying solely on concentration thresholds;
– deepening theoretical modeling through stochastic–neural hybridization.

The system's distributed architecture also enhances spatial sensitivity, enabling identification of localized emission sources that would otherwise remain undetected by centralized stations [6].

***Conclusion*.**

This research provides a scientifically grounded, technologically integrated framework for predictive

$$R(t) = w_1 \frac{C_{PM}(t)}{C^{PDK}PM} + w_2 \frac{CCO(t)}{C^{PDK}CO} + w_3 \frac{T(t)}{T\max} + w_4 A(t)$$

environmental monitoring at Waste-to-Energy facilities. The combination of a multi-sensor acquisition platform, stochastic concentration modeling, Kalman filtering, and neural forecasting establishes a pathway toward real-time risk anticipation and improved environmental governance. The methodology demonstrates potential for industrial deployment and for incorporation into national monitoring strategies aimed at modernizing ecological oversight and occupational safety in the WtE sector.

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