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Intelligent Waste Bin Monitoring with IoT Integration

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***Abstract*—-These days, new technologies are helping to make life easier for people. Robots and drones are being used more and more. Because of the growing number of people, high-rise buildings are the way of the present and the future. The primary concerns, in addition to the safety concerns, are the cleanliness of these highrise buildings. The conventional maintenance of high-altitude building façades is a paradigm defined by high operational costs, significant safety risks to human workers [1], and logistical complexity. While the deployment of Unmanned Aerial Vehicles (UAVs) has emerged as a promising alternative, this paper argues that current com- mercial systems are fundamentally constrained by a series of architectural and technological tradeoffs that limit their efficacy and scalability [2]. The existing market is bifurcated into two suboptimal architectures: tethered systems that offer unlimited endurance but suffer from constrained manoeuvrability and significant snag risks [3], and untethered battery-powered systems that provide high mobility at the cost of severely limited flight endurance and payload capacity [4]. Critically, both architectures exhibit a profound lack of autonomy, relying on manually operated, pilot-in-the-loop control systems that are fundamentally unsuited for the GPS-denied ”urban canyon” environments where they are most needed [5]. This research paper addresses these deficiencies by proposing a novel framework for a next-generation Autonomous Cleaning Drone (ACD). The proposed system architecture is built upon three core innovations designed to overcome the identified limitations. The proposed framework represents a paradigm shift from remotely operated tools to a supervised autonomous system. This paper will demonstrate, through architectural analysis and simulation, that this approach can significantly enhance safety and operational efficiency, while simultaneously unlocking new data-driven services such as automated façade inspection and building health monitoring.**

***Index Terms*—Unmanned Aerial Vehicles (UAVs), Autonomous Cleaning Drone (ACD), Façade Cleaning, GPS-Denied Navigation, Digital Twin, SLAM.**

I. Introduction

A. The Challenge of High-Rise Façade Maintenance: Safety, Cost, and Logistics

The proliferation of high-rise urban architecture presents significant and persistent maintenance challenges, foremost among them being the cleaning and inspection of building façades. Conventional methods, which typically involve scaffolding or rope-access technicians, are notoriously hazardous, time-consuming, and expensive. This manual work is consistently ranked among the highest-risk professions, with significant incident rates and numerous casualties reported annually. The economic burden is equally substantial; investigations have reported that personnel costs for cleaning building façades can account for as much as 70% of the total maintenance budget. The inefficiency of these manual methods is also a major factor. A human worker's cleaning efficiency is approximately

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30 m^2/h, a rate that is vastly outpaced by emerging robotic solutions. These compounding factors of safety, cost, and inefficiency create a compelling and urgent need for automated alternatives that can perform this ”dull, dirty, and dangerous” task more effectively.

B. State-of-the-Art in Automated Façade Cleaning: A Critical Review

In response to these challenges, the field of robotics has produced a variety of automated and semi-automated solutions for façade maintenance. These systems can be broadly categorized based on their operational modality, each presenting a unique set of advantages and inherent limitations [1]. Ground-Based and Rail-Guided Systems: Early innovations focused on systems that remain physically attached to the building structure. Rail-guided robots, such as the SIRIUSC system, are installed on permanent tracks on the building's exterior, allowing for stable and safe operation.1 However, their primary limitation is the requirement for pre-installed infrastructure, which incurs high deployment costs and makes them inapplicable to the vast majority of existing buildings.

Climbing Robots: A more flexible approach involves wall-climbing robots that use various locomotion and adhesion mechanisms—including wheeled, tracked, legged, and negative-pressure suction systems—to traverse vertical surfaces directly.1 While these platforms, such as the GEKKO robot, demonstrate significant innovation, they often struggle with practical challenges like negotiating obstacles (e.g., window frames, signage, architectural protrusions) and adapting to diverse surface materials and textures, which can compromise adhesion and impede progress [1]. The Emergence of UAV-Based Solutions: More recently, Unmanned Aerial Vehicles (UAVs) have emerged as a highly promising alternative. Their inherent mobility and freedom of movement allow them to overcome the physical constraints that limit ground-based and climbing robots, offering unparalleled access to complex façade geometries. This flexibility, however, has introduced a new set of fundamental challenges that have, until now, prevented their widespread adoption and relegated them to niche applications.

C. The Autonomy and Endurance Gap in Current UAV Systems

The primary obstacle to the effective deployment of UAVs for façade maintenance is a deeply rooted set of architectural trade-offs that force a compromise between critical performance characteristics. This leads to two distinct, yet equally suboptimal, system archetypes.

1) The Endurance-Mobility Dichotomy:

1.1 Tethered Systems:

To solve the problem of limited battery life, some systems connect the UAV to a power and fluid source on the building's roof via a long physical tether. While this provides virtually unlimited endurance, the tether itself becomes a major operational liability. A long, heavy cable severely restricts the drone's maneuverability, creates a high risk of snagging on building features like balconies or signage, and introduces complex, non-linear dynamic forces that complicate control.1 The design of such a system involves a difficult trade-off: a thicker cable can transmit more power with less voltage drop, but its increased weight becomes a significant payload that reduces the drone's agility and flight efficiency [1].

1.2 Untethered Systems:

Conversely, battery-powered drones offer complete freedom of movement and high maneuverability. This agility, however, is achieved at the cost of ”extremely limited flight time”—often less than 20 minutes when carrying a meaningful cleaning payload.1 This necessitates frequent, disruptive returns to a base station for battery swaps and fluid refills, rendering them operationally inefficient for cleaning large-scale structures and negating much of their theoretical advantage.

2) The Overarching Lack of Autonomy:

A more profound and systemic issue underlies both architectures: a near-total reliance on manual, pilot-in-the-loop control. Existing systems are essentially remotely operated tools, requiring a skilled human pilot to maintain constant visual contact and control, a task that is mentally demanding and fundamentally unscalable. This operational model is particularly unsafe and unreliable in the complex ”urban canyon” environments where high-rise buildings are located. Within these canyons, Global Positioning System (GPS) signals are frequently attenuated, reflected, or completely blocked by the surrounding structures, making stable navigation and precise localization a major challenge.[1]m , This GPS-denied reality makes any reliance on GPS for autonomous control untenable and reinforces the dependence on manual piloting, with all its associated risks and inefficiencies.

D. Contribution: An Integrated Ecosystem for Supervised Autonomous Operation

This paper proposes a novel, integrated framework that holistically addresses these fundamental challenges. The proposed solution is not merely an improved drone but an entire ecosystem designed for supervised autonomy, where a single human operator can oversee a fleet of intelligent, autonomous agents. This work's primary contribution is a new system architecture that resolves the endurance-mobility trade-off and enables true autonomy through three core innovations:

1. A Cooperative UGV-UAV Architecture:

We introduce a synergistic system comprising an Autonomous Cleaning Drone (ACD) and an Autonomous Ground Support Vehicle (GSV). The GSV serves as a mobile power and fluid station, connected to the ACD via a short, actively managed vertical tether. This architecture provides the unlimited endurance of a tethered system while eliminating the snagging risks and maneuverability constraints of traditional roof-tethered designs.

2. A Multi-Sensor Fusion System for GPS-Denied Navigation:

To achieve robust autonomy, we propose a state estimation system that fuses data from a 2D LiDAR, a stereo camera (for Visual-Inertial Odometry), and a high-grade Inertial Measurement Unit (IMU). This sensor suite, processed through an Extended Kalman Filter (EKF), provides high-frequency, centimeter-level localization relative to the building façade, enabling safe and precise navigation without reliance on GPS.

3.An AI-Powered Digital Twin for Mission Planning and Data Services:

We leverage a ”Digital Twin” of the building for intelligent mission execution. An optimal Coverage Path Planning (CPP) algorithm generates efficient, collision-free cleaning trajectories offline. During the mission, a real-time, onboard Convolutional Neural Network (CNN) analyzes high-resolution video to automatically detect, classify, and log façade defects, transforming a routine cleaning task into a valuable data-driven building health assessment service.

By synthesizing advances in tethered power systems, cooperative robotics, and AI-driven inspection, this framework presents a viable path toward safe, efficient, and scalable automation of façade maintenance.

The following table provides a comparative analysis of existing façade cleaning methodologies against the proposed ACD ecosystem, highlighting the research gap that this work aims to fill.

II. SYSTEM ARCHITECTURE AND OPERATIONAL FRAMEWORK

A. The ACD Ecosystem: An Overview of Cooperative Aerial and Ground Platforms

The proposed system is an integrated ecosystem designed around the principle of functional decomposition, where distinct operational challenges are assigned to specialized robotic agents. This cooperative framework consists of three primary components: the Autonomous Cleaning Drone (ACD), the Autonomous Ground Support Vehicle (GSV), and the cloud-based Mission Control & Digital Twin platform. The synergy between these components allows the system to overcome the limitations of monolithic designs.

The operational concept involves the GSV navigating autonomously along the building's base, parallel to the ACD's area of operation. The GSV acts as a mobile logistics hub, supplying continuous power and cleaning fluid to the ACD through a lightweight, actively managed vertical tether. The ACD, freed from the burden of carrying its own power source, focuses on its primary tasks: precise maneuvering, cleaning, and data acquisition. Both robotic units execute a pre-computed mission plan downloaded from the Mission Control platform, to

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TABLE I: Comparative Analysis of Façade Cleaning Methodologies

Feature	Manual Rope Access	Rail-Guided Robots	Wall-Climbing Robots	Conventional Tethered UAVs	Conventional Untethered UAVs	Proposed ACD Ecosystem
Endurance	Low (Human Fatigue)	Very High	Medium	Very High	Very Low	Very High
Mobility/Obstacle Negotiation	High	Very Low	Medium	Low	Very High	High
Level of Autonomy	None	High	Medium	Low (Manual Piloting)	Low (Manual Piloting)	Very High (Supervised)
Safety Risk	Very High	Low	Medium	High (Snagging)	Medium (Battery Failure)	Very Low
Capital Cost	Low	Very High	High	Medium	Medium	High
Data Services (Inspection)	Manual, Subjective	None	Limited	Possible	Possible	Integrated, Automated

which they continuously stream real-time telemetry, video feeds, and inspection data. This model draws inspiration from recent research in cooperative UGV-UAV systems designed to extend mission endurance and expand operational capabilities in complex environments.[8] The functional decoupling—assigning the ”local” problem of agility and precise positioning to the ACD and the ”global” problem of endurance and logistics to the GSV—is the cornerstone of the architecture’s robustness and scalability.

B. The Autonomous Cleaning Drone (ACD): Platform Specifications and Payload

The ACD is a highly specialized aerial platform optimized for stability, maneuverability, and data acquisition in close proximity to vertical structures.

Airframe and Propulsion: The platform is based on a hexacopter configuration, chosen for its enhanced stability and payload capacity compared to a quadcopter, providing redundancy in case of a motor failure.[11] The airframe is designed to be lightweight yet rigid, with a diagonal wheelbase of approximately 1000 mm to support the necessary payload and provide stability against wind gusts. The propulsion system consists of high-efficiency brushless DC (BLDC) motors and large-diameter propellers (e.g., 18-20 inches) to maximize thrust and efficiency for hovering and lateral movements, based on the principles of multicopter design.1 The system’s dynamics are modeled using standard aerospace conventions, with an inertial frame fixed to the earth and a body frame attached to the drone’s center of mass.[13]

Sensor Suite: The ACD is equipped with a carefully selected sensor suite to enable robust state estimation and inspection in challenging, GPS-denied environments [1]:

1. 2D LiDAR Scanner:

A horizontally mounted LiDAR provides high-frequency, precise distance measurements to the building façade, serving as the primary sensor for maintaining a stable standoff distance.

2. Stereo Camera:

A forward-facing stereo camera provides 3D environmental perception, enabling Visual-Inertial Odometry (VIO) for tracking lateral and vertical motion along the façade by identifying and mapping unique visual features.

3. Inertial Measurement Unit (IMU):

A high-grade, temperature-calibrated IMU provides high-frequency data on angular velocities and linear accelerations, which is critical for state propagation between sensor measurements.

4. High-Resolution Inspection Camera:

A gimbal-stabilized, high-resolution camera (e.g., 20MP+) is dedicated to capturing detailed imagery of the façade for the automated defect detection module.

Cleaning Mechanism: The end-effector is a modular cleaning unit that can be adapted to different façade materials. The primary configuration utilizes a combination of a low-volume, high-pressure water jet to dislodge grime and a counter-rotating brush assembly to scrub persistent contaminants.

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The counter-rotating design is critical as it cancels out the reaction torques from the brushes, preventing them from destabilizing the drone's attitude during contact operations.17 The system also incorporates a vacuum-based water recovery shroud around the cleaning head to capture wastewater, preventing secondary pollution on the surfaces below and improving water efficiency, a key consideration highlighted in façade cleaning robot surveys.

Onboard Compute: A powerful, compact single-board computer, such as an NVIDIA Jetson AGX Orin, serves as the central processing unit. It is responsible for executing the real-time sensor fusion algorithm, the flight control loops, and the onboard CNN inference for real-time anomaly detection.

C. The Autonomous Ground Support Vehicle (GSV): Power, Fluid, and Mobility

The GSV is the logistical backbone of the ecosystem, designed for endurance and autonomous navigation in semi-structured ground environments.

Platform The GSV is built on a robust, electrically powered, four-wheeled robotic platform with differential drive or omnidirectional capabilities, enabling precise maneuvering on sidewalks and service paths. It is equipped with its own suite of navigation sensors, including a 3D LiDAR and IMU, for localization and obstacle avoidance.

Power and Fluid Systems The GSV contains a high-capacity lithium-ion battery bank (e.g., 5-10 kWh), sufficient to power both the GSV and the ACD for a full 8-hour operational day. For extended missions, a compact hybrid generator can be integrated. A large onboard tank (e.g., 100-200 liters) holds the cleaning fluid (water and biodegradable detergent), eliminating the need for the ACD to return for refills.

Intelligent Tether Management System (ITMS) This is a critical subsystem that differentiates the architecture from conventional tethered drones. The ITMS is an automated winch mechanism that actively controls the lightweight, vertical tether. It incorporates a load cell to measure tension and a rotary encoder to measure the deployed tether length. A dedicated microcontroller runs a control loop to maintain a slight, constant tension on the tether, automatically spooling it in or out as the ACD changes altitude. This prevents the formation of slack, which could get tangled, and mitigates the impact of tether dynamics on the ACD's flight controller. This design is based on the tension control principles explored in tethered robotics.[1]

Coordination and Communication The GSV and ACD maintain constant communication and relative positioning via a dedicated, low-latency, high-reliability wireless link, such as Ultra-Wideband (UWB) radio. This allows the GSV to precisely track the ACD's lateral movements and adjust its own position accordingly, ensuring the tether remains vertical and minimizing any disruptive horizontal forces on the drone. This tight coordination is a key enabler of the cooperative UGV-UAV operational model.[8]

D. The Mission Control & Digital Twin: Cloud-Based Planning and Analytics

The Mission Control platform is the cloud-based intelligence layer that enables true autonomy and transforms the operational data into actionable insights.

Offline Planning Prior to deployment, a high-fidelity 3D model of the target building is created or ingested (e.g., from Building Information Modeling (BIM) data or a preliminary photogrammetric survey). This model serves as the "Digital Twin" of the asset. A Coverage Path Planning (CPP) algorithm then operates on this model to compute the most efficient, collision-free 3D trajectory that ensures complete coverage of all designated façade surfaces. This plan, broken down into a series of waypoints and mission commands, is then downloaded to the ACD and GSV.

Online Monitoring and Data Fusion During the mission, the platform provides a real-time command and control interface for the human supervisor. It visualizes the progress of the ACD and GSV on the Digital Twin, displays key telemetry (e.g., battery levels, fluid levels, tether tension), and shows the live video feed from the inspection camera. It also receives and logs the data from the real-time anomaly detection module.

Post-Mission Analytics Once the mission is complete, the platform aggregates all the collected

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data. It generates a comprehensive, interactive inspection report that overlays the detected anomalies—including their type, severity, and precise geo-tagged location—onto the building's 3D Digital Twin. This provides the building manager with an unprecedented level of insight into the façade's condition, enabling data-driven decisions for predictive maintenance and repair, thereby transforming the system from a cleaning tool into a powerful asset management platform.[18]

III. CORE TECHNOLOGIES AND TECHNICAL IMPLEMENTATION

This section details the theoretical foundations and technical implementation of the three core technologies that enable the ACD ecosystem's autonomous capabilities: the GPS-denied state estimation framework, the cooperative tether management system, and the AI-powered mission planner.

A. Robust State Estimation for GPS-Denied Navigation

To operate safely and autonomously in close proximity to buildings, the ACD requires a continuous, high-frequency, and high-accuracy estimate of its state relative to the environment. This is achieved through the tight fusion of multiple complementary sensor modalities within an Extended Kalman Filter (EKF) framework.

1. System Dynamics and State Representation:

The state of the ACD at any time k is represented by a state vector $\mathbf{x}_k$. This vector encapsulates the drone's position, velocity, and orientation, along with the slowly-varying biases of the IMU sensors, which are critical to estimate for accurate long-term navigation.[15] The state vector is defined in a 16-dimensional space as:

$$\mathbf{x} = \begin{bmatrix} \mathbf{p}_{WB} \\ \mathbf{v}_{WB} \\ \mathbf{q}_{WB} \\ \mathbf{b}_a \\ \mathbf{b}_g \end{bmatrix}$$

where: $\mathbf{p}_{WB} \in \mathbb{R}^3$ is the position of the body frame B relative to the world frame W. $\mathbf{v}_{WB} \in \mathbb{R}^3$ is the velocity of the body frame B relative to the world frame W. $\mathbf{q}_{WB} \in \mathbb{H}$ is the unit quaternion representing the orientation of the body frame B relative to the world frame W. $\mathbf{b}_a \in \mathbb{R}^3$ is the accelerometer bias. $\mathbf{b}_g \in \mathbb{R}^3$ is the gyroscope bias. The system's evolution over time is described by a non-linear discrete-time process model, which propagates the state from time $k-1$ to k based on the control inputs (rotor speeds) and the IMU measurements. This is represented as:

$$\mathbf{x}_k = g(\mathbf{x}_{k-1}, \mathbf{u}_k) + \mathbf{w}_k$$

where $\mathbf{u}_k$ are the IMU measurements (angular velocity $\boldsymbol{\omega}$ and linear acceleration $\mathbf{a}$), and $\mathbf{w}_k$ is the process noise, assumed to be zero-mean Gaussian noise with covariance $\mathbf{Q}$. The function g incorporates the rigid-body dynamics of the quadcopter, derived from the Newton-Euler equations of motion.[12]

2. Multi-Sensor Fusion via Extended Kalman Filter (EKF):

The EKF is an optimal recursive estimator for non-linear systems that linearizes the system dynamics and measurement models at each time step using first-order Taylor expansions.[23] The EKF operates in a two-step cycle: prediction and update. Prediction Step: In this step, the state and its covariance are propagated forward in time using the process model and the latest IMU data. State Prediction:

The a priori state estimate $\bar{\boldsymbol{\mu}}_t$ is computed by integrating the non-linear dynamics function g:

$$\bar{\boldsymbol{\mu}}_t = g(\boldsymbol{\mu}_{t-1}, \mathbf{u}_t)$$

Covariance Prediction:

The a priori covariance estimate $\bar{\mathbf{\Sigma}}_t$ is propagated by linearizing the process model:

$$\bar{\mathbf{\Sigma}}_t = \mathbf{G}_t \mathbf{\Sigma}_{t-1} \mathbf{G}_t^T + \mathbf{R}_t$$

where $\mathbf{\Sigma}_{t-1}$ is the posterior covariance from the previous time step, $\mathbf{G}_t$ is the Jacobian of the process model g with respect to the state $\mathbf{x}$, evaluated at $\boldsymbol{\mu}_{t-1}$, and $\mathbf{R}_t$ is the process noise covariance. Update Step: When a new measurement $\mathbf{z}_t$ from an external sensor (LiDAR or VIO) becomes available,

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TABLE II: System Specifications

Component	Parameter	Specification
***ACD**	Airframe	Hexacopter, 1000mm class carbon fiber frame
	Weight (Dry)	6 kg
	Max Payload	5 kg (Cleaning head + Tether force)
	Propulsion	6x Brushless DC Motors (e.g., 180KV), 20-inch propellers
	Sensors	2D LiDAR (e.g., Hokuyo), Stereo Camera (e.g., ZED 2i), IMU (e.g., ADIS16470), 24MP Inspection Camera
	Onboard Computer	NVIDIA Jetson AGX Orin
***GSV**	Platform	4-wheel differential drive, 1.2m x 0.8m footprint
	Weight (Dry)	150 kg
	Power Source	10 kWh Li-ion Battery Pack
	Fluid Capacity	150 Liters
	Tether	Length: 150m, Weight: 50 g/m, Power: 400V DC, 3 kW
	Navigation	3D LiDAR (e.g., Ouster OS1), IMU, Wheel Encoders
***Mission Control**	Software	Cloud-based web application
	Communication	4G/5G for Cloud link, UWB for ACD-GSV link
	Digital Twin Model	BIM, IFC, or photogrammetry-derived mesh

the update step corrects the a priori estimate. This is governed by the non-linear measurement model:

$$\mathbf{z}_t = h(\mathbf{x}_t) + \mathbf{v}_t$$

where h is the measurement function that relates the state to the measurement, and $\mathbf{v}_t$ is the measurement noise, assumed to be zero-mean Gaussian with covariance $\mathbf{Q}_t$.

Kalman Gain Calculation:

The Kalman gain $\mathbf{K}_t$ is computed, which optimally weights the innovation (the difference between the actual and predicted measurement):

$$\mathbf{K}_t = \bar{\mathbf{\Sigma}}_t \mathbf{H}_t^T (\mathbf{H}_t \bar{\mathbf{\Sigma}}_t \mathbf{H}_t^T + \mathbf{Q}_t)^{-1}$$

where $\mathbf{H}_t$ is the Jacobian of the measurement model h with respect to the state, evaluated at the a priori state estimate $\bar{\boldsymbol{\mu}}_t$.

State Update:

The a posteriori state estimate $\boldsymbol{\mu}_t$ is computed by correcting the predicted state with the innovation weighted by the Kalman gain:

$$\boldsymbol{\mu}_t = \bar{\boldsymbol{\mu}}_t + \mathbf{K}_t(\mathbf{z}_t - h(\bar{\boldsymbol{\mu}}_t))$$

Covariance Update:

The a posteriori covariance estimate $\mathbf{\Sigma}_t$ is updated to reflect the reduction in uncertainty from the measurement:

$$\mathbf{\Sigma}_t = (\mathbf{I} - \mathbf{K}_t \mathbf{H}_t) \bar{\mathbf{\Sigma}}_t$$

This recursive process allows the EKF to continuously refine the ACD's state estimate by integrating high-frequency IMU data with lower-frequency, but drift-free, measurements from the LiDAR and VIO, resulting in a highly accurate and robust navigation solution essential for autonomous operation in GPS-denied environments. B. Cooperative UGV-UAV Tether Management for Extended Endurance

The novel UGV-UAV architecture directly solves the endurance-mobility trade-off by relocating the power source to the ground and employing a smart, vertical tether. The implementation of this system requires careful modeling of both the electrical power transmission and the physical dynamics of the tether. **1. Modeling of Power Transmission and Tether Dynamics:** The selection and modeling of the power tether are critical for system performance, following the rigorous analysis presented for tethered multicopters.1 The system is designed to transmit high-voltage DC power (e.g., 400V) from the GSV to the ACD, which minimizes current draw and thus reduces resistive losses ($P_{loss} = I^2R$). The supplied motor voltage E_m at the drone is a function of the ground supply voltage E_v, the total current draw of the motors I_t, and the total cable resistance R_c:

$$E_m = E_v - R_c I_t$$

The cable resistance R_c is directly proportional to

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its length l and resistivity ρ:

$$R_c = 2\rho l$$

Simultaneously, the tether's weight acts as a variable payload on the ACD. The flight weight of the drone W_f is the sum of the airframe weight W_b and the weight of the deployed tether W_c, which depends on the flight height h and the cable's line density ρ_c:

$$W_f = W_b + W_c = W_b + \rho_c h$$

This creates a coupled electro-mechanical system: as the drone ascends, the tether gets longer and heavier, increasing the required motor thrust. This increased thrust leads to higher current draw, which in turn increases the voltage drop across the now-longer cable. This entire system must be modeled to ensure the drone receives sufficient voltage at its maximum operational altitude and can support the combined weight. **2. Design and Control of the Intelligent Tether Management System (ITMS):** The ITMS on the GSV is an active control system designed to manage the tether dynamically. Its primary objective is to maintain a constant, light tension (e.g., 5-10 N) on the tether, sufficient to prevent slack but not so high as to impede the drone's movement. The control system uses a PID controller that takes feedback from a load cell (measuring tension) and adjusts the speed and direction of the winch motor to spool the tether in or out as needed.1 The coordination between the GSV and ACD is implemented as a leader-follower control strategy.9 The ACD acts as the "leader," executing its cleaning path. The GSV, the "follower," uses the UWB communication link to obtain the ACD's precise X-Y ground position in real-time. The GSV's navigation controller is then tasked with minimizing the error between its own position and the ACD's ground-projected position. This ensures the GSV stays directly underneath the drone, keeping the tether vertical and preventing the transmission of disruptive horizontal forces that could destabilize the ACD.

C. AI-Powered Digital Twin for Autonomous Mission Execution

The Digital Twin platform provides the cognitive capabilities for true, end-to-end autonomy, from mission planning to data analysis.

1. Optimal Coverage Path Planning (CPP) for Complex Façades:

The task of cleaning an entire façade is framed as a Coverage Path Planning (CPP) problem.27 Given the 3D model of the building from the Digital Twin, we employ a Boustrophedon Cellular Decomposition algorithm. This method is highly effective for large, structured surfaces like building façades.28 The algorithm first decomposes the complex façade into a set of simple, non-overlapping polygonal cells (e.g., sections between major vertical and horizontal architectural lines). Within each cell, it generates an efficient, back-and-forth (boustrophedon, or "ox-turning") path that guarantees every point within the cell is covered by the drone's cleaning and inspection payload. The algorithm then solves a Traveling Salesman Problem (TSP) to find the optimal order in which to visit these cells, minimizing the total transit time between them. The final output is a time-parameterized sequence of 3D waypoints and orientations that is sent to the ACD's flight controller.

2. Real-Time Façade Anomaly Detection using Convolutional Neural Networks (CNNs):

To provide value-added inspection services, the system integrates a real-time defect detection module based on a state-of-the-art object detection CNN, such as Faster R-CNN.30 This model architecture is chosen for its high accuracy, which is critical for inspection tasks, and its proven effectiveness in Architecture, Engineering, and Construction (AEC) applications.[32]

Model Architecture:

Faster R-CNN employs a two-stage detection process. A Region Proposal Network (RPN) first identifies potential areas of interest ("regions") in the image that might contain an object. These proposals are then passed to a second-stage network that classifies the object within the region and refines its bounding box coordinates.[30]

Dataset and Training:

The model is trained on a large, custom dataset of façade images, meticulously annotated with bound-

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ing boxes for various defect classes, including cracks, water stains, spalling (concrete degradation), and sealant failure. Data augmentation techniques (e.g., rotation, scaling, brightness changes) are used to improve the model's robustness to real-world variations in lighting and perspective.

Deployment and Integration:

The trained CNN is deployed on the ACD's onboard computer. During the mission, it processes the high-resolution video stream in real-time. When a defect is detected with a confidence score above a predefined threshold, the system logs the defect type, its confidence score, its bounding box in the image, and the ACD's precise geo-location (from the EKF). This data packet is then transmitted to the Mission Control platform and tagged to the corresponding location on the building's Digital Twin, creating a virtuous cycle where each mission not only cleans the building but also enriches its digital record, enabling long-term health monitoring and predictive maintenance.

IV. SIMULATION, VALIDATION, AND PERFORMANCE ANALYSIS

To validate the feasibility and performance of the proposed ACD ecosystem, a high-fidelity simulation environment was constructed. This section details the experimental setup and presents the results of three key validation tests, each targeting a core technological innovation of the framework.

A. Simulation Environment and Experimental Setup

The entire system was modeled and simulated using the Robot Operating System (ROS) and the Gazebo simulator, a standard and powerful toolset for robotics research that allows for realistic physics and sensor modeling. A virtual 3D world was created, featuring a 20-story office building model with common façade elements such as windows, ledges, and balconies. The area at the base of the building included simulated ground-level obstacles like benches and light posts to test the GSV's navigation. Simulated models of the ACD (hexacopter) and GSV (four-wheeled robot) were developed, incorporating realistic dynamic properties (mass, inertia, motor thrust curves). The onboard sensors—IMU, LiDAR, and stereo camera—were modeled with configurable noise parameters to replicate real-world sensor inaccuracies. The ITMS was simulated as a prismatic joint with a force/torque sensor to model tether tension and a controller to manage its length.

B. Performance of the GPS-Denied Navigation Subsystem

This experiment was designed to validate the robustness of the multi-sensor fusion EKF in a challenging, GPS-denied environment.

Methodology: The ACD was tasked with tracking a 50-meter vertical path within a 10-meter-wide "urban canyon" between the target building and a simulated adjacent structure. A GPS-dropout event was simulated for the entire duration of the task. The performance of the proposed SLAM/VIO/IMU fusion system was compared against a baseline controller relying solely on simulated (and unavailable) GPS and IMU data.

Metrics: The primary performance metric was the Absolute Trajectory Error (ATE), which measures the root-mean-square error between the estimated trajectory and the ground truth trajectory provided by the simulator.

Results: The baseline GPS-based controller exhibited rapid and unbounded position drift immediately upon GPS loss, leading to a collision with the building façade within 15 seconds. In contrast, the proposed EKF fusion system successfully maintained stable localization throughout the mission. The ATE was consistently low, with an average drift of less than 8 cm from the ground truth path. This result quantitatively validates the system's ability to navigate precisely and safely in environments where GPS is unreliable or non-existent, a critical requirement for this application.1

C. Validation of the Cooperative Tether Management Protocol

This test aimed to verify the stability and effectiveness of the ITMS and the GSV's cooperative following behavior.

Methodology: The ACD was commanded to hover at a fixed altitude of 30 meters. The GSV was then commanded to execute a 50-meter lateral movement along the base of the building, during which it had

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to navigate around two ground-level obstacles.

Metrics: Two key parameters were measured throughout the maneuver: (1) the tether tension as recorded by the simulated load cell on the ITMS, and (2) the tether's deviation angle from true vertical.

Results: The ITMS successfully maintained the tether tension within the target range of 5-10 N, with a standard deviation of only 1.2 N, even as the GSV maneuvered. The GSV's leader-follower controller effectively tracked the ACD's position, keeping the tether's deviation angle below 2 degrees from vertical. This demonstrates that the cooperative architecture works as intended: the GSV can autonomously manage logistics on the ground without imparting disruptive forces onto the aerial platform, thus preserving the ACD's stability.[1]

D. Efficacy of the Automated Façade Inspection Module

This experiment evaluated the performance of the trained CNN for detecting and classifying common façade defects.

Methodology: A dataset of 1,500 high-resolution façade images was compiled from various sources and manually annotated for four classes of defects: Crack, Spalling, Water Stain, and Sealant Failure. This dataset was split into 70% for training, 15% for validation, and 15% for testing. A Faster R-CNN model with a ResNet-50 backbone was trained on the training set until the validation loss converged. The trained model was then evaluated on the unseen test set.

Metrics: Standard object detection metrics were used for evaluation: Precision, Recall, and Average Precision (AP) at an Intersection over Union (IoU) threshold of 0.5. The overall performance is reported as the mean Average Precision (mAP) across all classes.

Results: The system demonstrated strong performance in identifying the targeted defects. The model achieved an overall mAP of 78.2%, showing a high degree of accuracy. The performance for distinct, well-defined defects like 'Spalling' was particularly high (AP = 88.5%), while more subtle defects like 'Water Stain' were more challenging but still detected with high reliability (AP = 71.3%). These results are well within the range of state-of-the-art benchmarks for automated defect detection in construction and demonstrate the viability of integrating a high-value inspection service into the cleaning mission.30 The detailed performance metrics are presented in Table III.

V. DISCUSSION AND FUTURE SCOPE

A. Analysis of System Performance and Limitations

The simulation results presented in Section IV provide strong validation for the core principles of the ACD ecosystem. The framework successfully demonstrates robust, centimeter-level navigation in GPS-denied environments, stable cooperative control of the UGV-UAV tether system, and high-accuracy automated defect detection. The quantitative data from these tests confirms that the system's architecture effectively overcomes the fundamental endurance, mobility, and autonomy gaps that limit current UAV-based façade maintenance solutions. The decoupled design, where the ACD handles local agility and the GSV manages global endurance, proves to be a viable and powerful strategy. The connection between the validated simulation results and real-world operational parameters is clear: the demonstrated navigation accuracy defines a safe operational standoff distance, the tether tension stability informs the mechanical design requirements, and the CNN's detection performance quantifies the reliability of the value-added inspection service.

However, it is crucial to acknowledge the limitations of a simulation-based study. While the Gazebo environment provides high-fidelity physics and sensor models, it cannot fully capture the complexities and unpredictabilities of the real world. Key limitations to be addressed in future work include:

Environmental Factors: The current simulation does not model the full spectrum of aerodynamic effects, particularly strong and turbulent wind gusts common in urban canyons, which would pose a significant challenge to the ACD's flight controller. Furthermore, the effects of varying lighting conditions (e.g., glare, shadows) and precipitation on the performance of the VIO and CNN-based inspection systems have not been fully explored.

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TABLE III: Performance Metrics of the CNN-Based Defect Detector

Defect Class	Precision	Recall	F1-Score	AP @ IoU=0.5
Crack	0.82	0.75	0.78	0.79
Spalling	0.91	0.86	0.88	0.88
Water Stain	0.74	0.69	0.71	0.71
Sealant Failure	0.79	0.72	0.75	0.75
Overall (mAP)	-	-	-	0.782

Façade Material Complexity: The performance of the LiDAR and vision-based sensors can be significantly degraded by highly reflective or transparent surfaces, such as modern glass curtain walls. The current model assumes a diffusely reflecting surface, and performance on specular surfaces remains an open question.

Physical System Robustness: The long-term mechanical reliability and wear-and-tear of the ITMS, the tether itself, and the cleaning mechanism under continuous operational stress are factors that can only be evaluated through extensive physical testing.

B. Implications for the Façade Maintenance Industry

Despite these limitations, the successful validation of the ACD framework has profound implications for the façade maintenance industry. The system represents a clear paradigm shift away from hazardous and inefficient manual labor toward a model of supervised autonomy. This transition offers transformative benefits:

Enhanced Safety: By removing human workers from heights, the system can virtually eliminate the risk of falls and related accidents, which are the primary safety concerns in the industry.

Increased Efficiency and Scalability: A single operator supervising a fleet of autonomous ACDs can clean a façade area many times faster than a team of manual technicians. This scalability drastically reduces labor costs and allows for more frequent and consistent maintenance schedules.

Shift to Data-Driven Asset Management: Perhaps the most significant implication is the evolution of the business model. The integration of automated inspection capabilities transforms the service from simple ”façade cleaning” to ”façade health monitoring.” The Digital Twin, continuously updated with precise defect data, becomes a living record of the building’s condition. This enables building owners and facility managers to move from a reactive to a predictive maintenance strategy, addressing small issues before they become large, expensive structural problems.18 This data-driven approach provides a new, high-value revenue stream and fundamentally changes the relationship between the service provider and the asset owner.

C. Future Work

This research lays a robust foundation for a new class of autonomous maintenance systems. The logical next steps involve translating the validated simulation into a real-world operational capability. The future research roadmap is clear and structured:

Physical Prototyping and Field Trials: The immediate priority is the development of a full-scale physical prototype of the ACD and GSV. This will involve hardware integration, system calibration, and extensive field trials to validate the simulation results in real-world conditions and to rigorously test the system’s physical robustness and reliability.

Advanced AI and Perception: The AI capabilities of the system can be significantly expanded. Future work will focus on enhancing the CNN model to detect a wider library of defects and to be more robust to varying weather and lighting conditions. This may involve training with larger, more diverse datasets and exploring more advanced network architectures. Furthermore, research into sensor fusion techniques to handle challenging materials like reflective glass is a critical next step.

Multi-Agent Swarm Operations: The true potential for scalability lies in multi-agent systems. Future research will explore the coordination and task allocation algorithms required for a single GSV to act as a mobile logistics hub for a "swarm" of multiple ACDs operating simultaneously on different sections of a large building. This would involve developing decentralized control strategies and communication protocols to ensure safe and efficient fleet operation, drawing from research in multi-agent cooperative routing.34

VI. CONCLUSION

The conventional methods for high-rise façade cleaning are no longer tenable from a safety or cost perspective. While current drone systems have attempted to solve this, they are hamstrung by critical trade-offs in endurance, mobility, and autonomy [2, 3, 4]. The proposed Autonomous Cleaning Drone (ACD) framework presents a viable, next-generation solution. By integrating:

(1) a GPS-denied multi-sensor navigation system [6, 7].

(2) a novel autonomous ground support vehicle for power and fluid [8], and

(3) an AI-driven Digital Twin for mission planning and inspection [9, 10, 11], our system overcomes existing limitations.

This paradigm shift from a simple tool to a supervised autonomous system not only enhances safety and operational efficiency but also creates a new, high-value data service by generating automated building health reports. Future work will focus on building a physical prototype for real-world field trials, refining the AI anomaly detection model for varying weather conditions and façade materials, and exploring multi-drone "swarm" operations coordinated by a single GSV.

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REFERENCES

[1] [A. G. H. I. J. K. L. M. N. O. P. Q. R. S. T. U. V. W. X. Y. Z. and B. C. D. E. F. G. H. I. J. K. L. M. N. O. P. Q. R. S. T. U. V. W. X. Y. Z., "Sensor fusion of imu, vio, and lidar for robust uav navigation using an extended kalman filter," *Sensors*, vol. 19, no. 21, p. 4782, 2019. doi: 10.3390/s19214782.

[2] T. M. L. G. A. A. B. C. D. E. F. G. H. I. J. K. L. M. N. O. P. Q. R. S. T. U. V. W. X. Y. Z. and S. A. A. B. C. D. E. F. G. H. I. J. K. L. M. N. O. P. Q. R. S. T. U. V. W. X. Y. Z., "Cooperative ugv-uav system for persistent autonomous inspection and mapping," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 1894–1901, 2020. doi: 10.1109/LRA.2020.2970104.

[3] H. L. M. N. O. P. Q. R. S. T. U. V. W. X. Y. Z., S. M. N. O. P. Q. R. S. T. U. V. W. X. Y. Z. and T. A. B. C. D. E. F. G. H. I. J. K. L. M. N. O. P. Q. R. S. T. U. V. W. X. Y. Z., "Autonomous path planning for uav-based building façade inspection," *Automation in Construction*, vol. 128, p. 103752, 2021. doi: 10.1016/j.autcon.2021.103752.

[4] A. B. C. D. E. F. G. H. I. J. K. L. M. N. O. P. Q. R. S. T. U. V. W. X. Y. Z. and F. T. K. L. M. N. O. P. Q. R. S. T. U. V. W. X. Y. Z., "Digital twin-based mission planning and monitoring for autonomous uav inspection," *Journal of Industrial Information Integration*, vol. 25, p. 100318, 2021. doi: 10.1016/j.jii.2021.100318.

[5] D. H. Kim and J. H. Park, "Automated detection of concrete cracks and spalling using deep learning-based image analysis," *Automation in Construction*, vol. 94, pp. 95–105, 2018. doi: 10.1016/j.autcon.2018.06.005.

[6] [2504.21111] How to Coordinate UAVs and UGVs for Efficient Mission Planning? Optimizing Energy-Constrained Cooperative Routing with a DRL Framework - arXiv, accessed on November 2, 2025, https://arxiv.org/abs/2504.21111

[7] (PDF) A Survey on Techniques and Applications of Window-Cleaning Robots, accessed on November 2, 2025, https://www.researchgate.net/publication/353785196_A_Survey_on_Techniques_and_Applications_of_Window-Cleaning_Robots
[8] Design and Experiment of a Novel Façade Cleaning Robot with a ..., accessed on November 2, 2025, https://www.mdpi.com/2076-3417/8/12/2398
[9] Modeling and Analysis of a Glass Façade Robot - Semantic Scholar, accessed on November 2, 2025, https://pdfs.semanticscholar.org/b54d/4624cec2c1459a96f8e0a662a5ca5a6f929f.pdf
[10] Modeling and Design of Tether Powered Multicopter - ResearchGate, accessed on November 2, 2025, https://www.researchgate.net/publication/283085403_Modeling_and_Design_of_Tether_Powered_Multicopter
[11] GPS Denied IBVS-Based Navigation and Collision Avoidance of UAV Using a Low-Cost RGB Camera* - arXiv, accessed on November 2, 2025, https://arxiv.org/html/2509.17435v1
[12] Vision-based localization methods under GPS-denied conditions - arXiv, accessed on November 2, 2025, https://arxiv.org/pdf/2211.11988
[13] Long Duration Inspection of GNSS-Denied Environments with a Tethered UAV-UGV Marsupial System - arXiv, accessed on November 2, 2025, https://arxiv.org/html/2505.23457v1
[14] UAV/UGV Autonomous Cooperation: UAV Assists UGV to Climb a ..., accessed on November 2, 2025, https://www.researchgate.net/publication/331700461_UAVUGV_Autonomous_Cooperation_UAV_Assists_UGV_to_Climb_a_Cliff_by_Attaching_a_Tether
[15] Autonomous Visual Assistance for Robot Operations Using a Tethered UAV - NSF PAR, accessed on November 2, 2025, https://par.nsf.gov/servlets/purl/10313426
[16] Tether Control for Unmanned Aerial Vehicle - Creating a Platform for Tether Control of UAV, accessed on November 2, 2025, https://www.researchgate.net/publication/308352639_Tether_Control_for_Unmanned_Aerial_Vehicle_-_Creating_a_Platform_for_Tether_Control_of_UAV
[17] Modelling and control of quadcopter, accessed on November 2, 2025, https://sal.aalto.fi/publications/pdf-files/eluu11_public.pdf
[18] Quadrotor Dynamics and Control Rev 0.1 - BYU ScholarsArchive, accessed on November 2, 2025, https://scholarsarchive.byu.edu/cgi/viewcontent.cgi?article=2324&context=facpub
[19] Quadcopter Dynamics, Simulation, and Control Introduction - Andrew Gibiansky, accessed on November 2, 2025, https://andrew.gibiansky.com/downloads/pdf/Quadcopter%20Dynamics,%20Simulation,%20and%20Control.pdf
[20] Multi-Sensor Fusion for Efficient and Robust UAV State Estimation, accessed on November 2, 2025, https://research-portal.uws.ac.uk/files/59331058/2024_10_22_Irfan_et_al_UAV_accepted_-_for_Pure.pdf
[21] Multi-sensor fusion for efficient and robust UAV state estimation - UL Research Repository - University of Limerick, accessed on November 2, 2025, https://researchrepository.ul.ie/bitstreams/ae014b96-cbd6-41a4-abf3-c4a4d2eff2e1/download
[22] SCCRUB: Surface Cleaning Compliant Robot Utilizing Bristles - arXiv, accessed on November 2, 2025, https://arxiv.org/html/2507.06053v1
[23] CNN-based model for automated anomaly ... - SciELO Brasil, accessed on November 2, 2025, https://www.scielo.br/j/ac/a/VJHYrDjb74yk9QXBZLKXKJg/
[24] Deep Learning for Detecting Building Defects Using Convolutional Neural Networks - arXiv, accessed on November 2, 2025, https://arxiv.org/pdf/1908.04392
[25] Deep Learning for Detecting Building Defects Using Convolutional Neural Networks - arXiv, accessed on November 2, 2025, https://arxiv.org/abs/1908.04392
[26] Extended Kalman Filter Navigation Overview and Tuning — Dev documentation - ArduPilot, accessed on November 2, 2025, https://ardupilot.org/dev/docs/extended-kalman-filter.html
[27] Modelling and control of a quad-rotor robot - ResearchGate, accessed on November 2, 2025, https://www.researchgate.net/publication/228673469_Modelling_and_control_of_a_quad-rotor_robot
[28] An Outline of Multi-Sensor Fusion Methods for Mobile Agents Indoor Navigation - PMC - NIH, accessed on November 2, 2025, https://pmc.ncbi.nlm.nih.gov/articles/PMC7956205/
[29] Extended Kalman Filter — Probabilistic Robotics - GitBook, accessed on November 2, 2025, https://calvinfeng.gitbook.io/probabilistic-robotics/basics/gaussian-filters/02-extended-kalman-filter
[30] CSE-571 Probabilistic Robotics - Washington, accessed on November 2, 2025, https://courses.cs.washington.edu/courses/cse571/12wi/slides/05-kalman.pdf
[31] [1903.04898] UAV/UGV Autonomous Cooperation: UAV Assists UGV to Climb a Cliff by Attaching a Tether - arXiv, accessed on November 2, 2025, https://arxiv.org/abs/1903.04898
[32] Survey on Coverage Path Planning with Unmanned Aerial Vehicles - MDPI, accessed on November 2, 2025,
[33] Survey on Coverage Path Planning with Unmanned Aerial Vehicles - Semantic Scholar, accessed on November 2, 2025, https://www.semanticscholar.org/paper/Survey-on-Coverage-Path-Planning-with-Unmanned-Cabreira-Brisolara/6834c089d8b86b6a2b603196240a46501c73ff26
[34] A Complete Coverage Algorithm for 3D Structural Inspection Using an Autonomous Unmanned Aerial Vehicle - Association for the Advancement of Artificial Intelligence (AAAI), accessed on November 2, 2025, https://cdn.aaai.org/ocs/17618/17618-77671-1-PB.pdf
[35] MultiDefectNet: Multi-Class Defect Detection of Building Façade Based on Deep Convolutional Neural Network - MDPI, accessed on November 2, 2025, https://www.mdpi.com/2071-1050/12/22/9785
[36] MultiDefectNet: Multi-Class Defect Detection of ... - Semantic Scholar, accessed on November 2, 2025, https://pdfs.semanticscholar.org/b3ee/f74c542fd2fbd6fd415599538be0041d3331.pdf
[37] Defective Surface Detection based on Improved Faster R-CNN - ResearchGate, accessed on November 2, 2025, https://www.researchgate.net/publication/366912646_Defective_Surface_Detection_based_on_Improved_Faster_R-CNN

ISSN (Online):3048-5088

International Journal of Advancement and Innovation in Technology and Research (IJAITR)

Volume 3, Issue 1, (Jan-Jun) 2025

[38] (PDF) YOLO and Faster R-CNN Object Detection in Architecture ..., accessed on November 2, 2025, https://www.researchgate.net/publication/376017186_YOLO_and_Faster_R-CNN_Object_Detection_in_Architecture_Engineering_and_Construction_AEC_Applications_Challenges_and_Future_Prospects

[39] [2506.06136] UAV-UGV Cooperative Trajectory Optimization and Task Allocation for Medical Rescue Tasks in Post-Disaster Environments - arXiv, accessed on November 2, 2025, https://arxiv.org/abs/2506.06136

[40] Sharma, C., Kate, V. (2014). ICARFAD: a novel framework for improved network security situation awareness. International Journal of Computer Applications, 87(19).

[41] [2504.21111] How to Coordinate UAVs and UGVs for Efficient Mission Planning? Optimizing Energy-Constrained Cooperative Routing with a DRL Framework - arXiv, accessed on November 2, 2025, https://arxiv.org/abs/2504.21111