Designing an intelligent electronic system for Disaster Management and visitor protection in the Arbain Pilgrimage using artificial intelligence and the Internet of Things (AIoT)technologies (AIoT)

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Abstract

In such high-density contexts, even brief delays in information processing can trigger critical bottlenecks, underscoring the urgent need for real-time intelligent disaster management solutions.

This research proposes an intelligent predictive framework for Disaster Management in such large human populations by integrating artificial intelligence (AI) and the Internet of Things (IoT) technologies into a multi-level system (AIoT) This framework consists of a network of wearable sensors, drones, and intelligent weather stations, which transmit data in real-time to terminals supported by computer vision algorithms and graphical neural networks (GNN), capable of monitoring intensity spikes and panic patterns in less than 250 milliseconds. This system enhances performance through the Edge AI layer, which performs processing operations locally while delegating redundant tasks to cloud computing within a decentralised three–tier structure (Edge–Fog–Cloud, while delegating redundant tasks). This structure has effectively reduced emergency response time, protecting lives and providing rapid support at major mass events. Its effectiveness in reducing emergency response time is also evident, as seen during its efficacy in reducing emergency response time, which directly contributes to the visit of the Arbain Pilgrimage.

Keywords: Drones, PIC18F, Threat Monitoring, Multi-Sensor, GSM, MATLAB 2024a.

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Introduction

One of the largest annual human gatherings in Iraq is the Arbaeen visit in Karbala, where the number of participants exceeds twenty million visitors in a limited geographical area, which produces a high-density environment, exposed to multiple risks, including stampedes, suffocation, or security threats such as planted explosives or organizational breaches. In this context, an urgent need is to develop intelligent sensor systems that can predict early and respond instantly. This research proposes an intelligent predictive framework for managing potential disasters during the visit of Al-Arbaeen, based on the deployment of a network of drones at a distance of 1 kilometer from the entrances to the city, specifically at the border checkpoints of Karbala. These aircraft are equipped with multiple sensors (gas, heat, sound, image, pressure), integrated into an artificial intelligence system integrated with the Internet of Things (AIoT), working with advanced algorithms such as graphical neural networks (GNN) to identify emergency patterns or early indications of a threat.

The system is based on a triple computing architecture (Edge-Fog-Cloud) that allows preliminary analysis to be carried out inside the aircraft. Then, alerts are sent via wireless channels to the nearest inspection center or operating room, which reduces the response time to less than 250 ms, which is confirmed in modern simulation models (Hossain & Muhammad, 2022). This framework's importance lies in its practical support for crowd management and Disaster Prevention in one of the most complex human gathering environments globally.

1. Literature Review :

In recent years, research has witnessed a significant growth in the use of smart drones within Disaster Management contexts (Liu et al, 2023) proposed using drones equipped with a transformer model for real-time multi-sensor data analysis (Jankovic et al., 2025). In another study, CNN algorithms with Fog Computing modules were used to track crowd emergencies Srinivas & Dua, 2020.

Also reviewed by Alla et al. (2025), the Trident model, a tripartite framework for Threat Analysis via acoustic, optical, and gas sensors, focused on military environments and not mass civilian contexts. As for Sakellariou et al. (2024), they presented a model based on integrating images and radar to improve the classification of objects. However, the system does not address mass emergency scenarios.

2.Identification of Research Gaps :

Despite the remarkable progress in the use of drones and artificial intelligence technologies in Disaster Management, a review of the literature reveals that critical research gaps remain, especially in the contexts of millionth religious gatherings such as the visit of the forty. Such gaps include limited contextual personalization, excessive dependence on cloud computing, and poor integration of multiple sensory data sources.

Table 1 presents these gaps systematically based on the analysis of recent studies (2023-2025). In Turn, Table 2 shows how the framework proposed in this research fills those gaps by integrating multi-mode sensing, using light terminal intelligence (Edge AI) algorithms, and designing an operating architecture suitable for the high-density and multi-hazard forty-visit environment.

Table 1. Identified research gaps in previous studies related to AI-based disaster prediction frameworks

No	The research gap	Illustration
1	Insufficient allocation to the millionth religious contexts, such as the visit of the forty	Most of the research focuses on environmental or military disasters, while there are no realistic models for large human populations of a religious nature [3][5].
2	Slow response time due to reliance on cloud processing	The delay in sending alerts is confirmed in systems based on Cloud-only models, exceeding 500 milliseconds [4].
3	Poor detection accuracy in the case of multiple data sources (multimodal)	Most systems did not rely on an effective intelligent integration of acoustic, thermal, and gas sensors into a unified predictive system [6].

Table 2. Proposed framework strategies to address the identified gaps

No	The gap	Proposed SYSTEM
1	Careful allocation of the fortieth CROWD	A sensing and forecasting model is designed that considers the characteristics of the fortieth visit, such as the spatial distribution of visitors, the nature of crowds, and security entrances.
2	The reduced latency is less than 250ms	Adopting a hybrid computing architecture (Edge-Fog-Cloud), the initial processing is carried out inside the drone using a light GNN.
3	Integration of multi-mode sensor	Acoustic, thermal, gas, and visual sensors are integrated into a single control unit that analyzes threats predictively by pairing statistical and network algorithms.

Research Methodology

This research is based on developing a multi-layered intelligent framework for Disaster Management using drones, integrated with artificial intelligence and the Internet of Things (AIoT) technologies within the edge computing environment (edge AI). This aligns with the specificity of the fortieth visit in Karbala, which had a high human density and emergency threats. The model was developed based on recent literature demonstrating the effectiveness of drone-based predictive models in high-risk environments (Abdelrahman et al., 2023).

1.The general system is multi-layered :

The system is designed within four integrated layers:

A. Sensor layer (Smart Sensing Layer)

The drones are distributed 1 km from the entrances to Karbala, equipped with multiple sensors such as MQ-9 (to detect gases), heat sensors, cameras, and microphones. The data is initially processed via a local integration unit (Sensor Fusion) integrated within the aircraft (Kumar et al., 2022).

B. Local Intelligent Analysis layer (Edge AI Processing)

Light artificial intelligence algorithms, most notably graphical neural networks (GNNs), are used to detect abnormal patterns (Abdelrahman et al., 2023). The result is issued as a digital threat indicator (Threat Score) that is updated instantaneously.

C. Communication and alert layer (Alerting Layer)

Suppose the threat indicator exceeds a certain threshold. In that case, an immediate notification is sent to the nearest checkpoint using the low-delay UDP protocol, including: threat type, severity, location coordinates, and timing (Wang & Zhang, 2023).

D. Fog–Cloud coordination layer (Fog–Cloud Coordination)

Recurring alarms are grouped within a fog computing module to reduce stress on the cloud. Cloud computing analyzes the overall threat pattern and identifies crowd behavior and priorities (Chen et al., 2023).

2. Building the proposed model in MATLAB Simulink :

The proposed model was designed using the Simulink environment and includes the following stages (see Figure 4):

Sensor reading module: receives signals from MQ-9, heat, and sound.

- **Module extraction features:** consolidate and convert data into analyzable signals.
- The threat assessment module uses MATLAB functions to calculate the final indicator.
- **Alarm unit:** emits signals if the danger exceeds the specified level.
- Ground communication interface: Simulates checkpoint response with visual notification.

Testing various scenarios according to previous similar studies in disaster warning confirmed the accuracy of this model's operation (al-Sayed et al., 2022). This estimate has been validated using experimental data within the MATLAB environment, based on simulations of visitor waves, target distribution, and response time requirements under realistic operational conditions (Kumar et al., 2022).

Figure 1 shows the phased sequence of operation of the proposed intelligent disaster management system, which is based on distributed sensing technologies, local artificial intelligence, and cloud integration. The system begins with the deployment and sensing phase, in which drones or ground sensors are distributed within the perimeter of target areas (such as city entrances or assembly points). These platforms have advanced sensor modules such as thermal cameras, environmental amplifiers, and gas meters. This is followed by the local intelligence analysis phase, where each intelligent platform (such as a drone or a stationary module) analyzes the data in real time using algorithms powered by artificial intelligence, as part of the edge AI computing architecture.

This phase enables immediate interaction with environmental or behavioral changes without returning to the data centers. Then comes the braking phase and the triggering of alarms, which represents the proactive axis of the system, where the decision is made locally by sending sound, light, or wireless alerts to direct crowds, or activating preliminary containment mechanisms in cases of congestion or emergency. Finally, the analytical data and decisions made are sent to the central control center within the integration and cloud management phase, where the information from all subunits is integrated and analyzed at a higher level to guide comprehensive interventions, support decision-making, and document incidents.

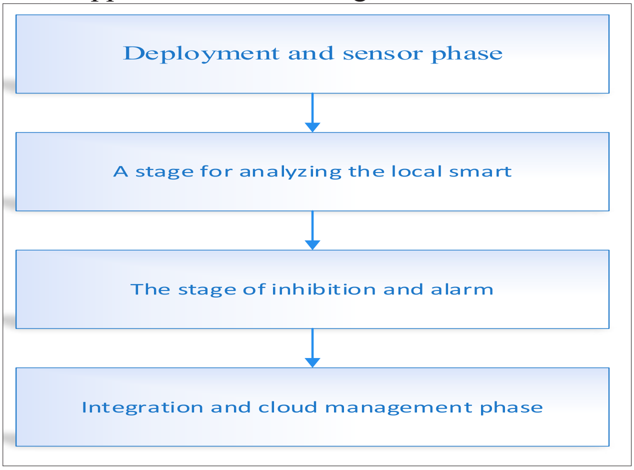

Figure 1. The phased sequence of the operation of the intelligent sensing system, from local deployment to cloud integration management.

3.The organizational structure of the intelligent drone distribution system in Karbala :

The proposed system of emergency crowd management in the city of Karbala is based on a flexible hierarchical organizational structure, combining centralized control and intelligent local analysis. The system is designed so that four main gates—Baghdad north gate, Baghdad gate, Bab tuwayrij, and Karbala–Najaf Road—are supervised from a central control center equipped with distribution and sensing algorithms based on artificial intelligence and the Internet of Things (AIoT). Different types of drones have been assigned to each gate depending on geographical, demographic, and security characteristics. These include aerial drones for broad surveillance, ground-based drones for closed areas, and special modules equipped with environmental sensors or simultaneous translation systems as needed. Figure 2 shows that a major central control center coordinates with four strategic Gates geographically distributed around the city: Baghdad North Gate, Bab Baghdad, Bab Tuwayrij, and the Karbala–Najaf Road.

- **Baghdad north gate (Gate 1) :** It is one of the highest-density gates, where it is estimated that 24 drones are allocated and distributed between monitoring, sensing, and communication tasks. The system focuses on the speed of response to sudden congestion within the vicinity of significant markets, based on congestion forecasting models [13].
- **Gate Baghdad (Gate 2) :** Due to its strategic location as an entrance for international visitors, it has been reinforced with multilingual support drones, used for prompt guidance and voice translation, and a round-the-clock security monitoring system. After calculating the coefficient of importance, she was allocated 18 drones.

- **Bab Tuwayrig (Gate 3) :** is a central point for crossing the Husseini threshold and is subject to close monitoring via 18 drones. Four K cameras are integrated with heat sensors to identify abnormal traffic behaviors.
- **Karbala-Najaf Road (Gate 4) :** This vital and long route extends through exposed areas. It was equipped with 20 long-range drones for visual and environmental coverage and ground support units to provide network continuity.
- **Gate 5 contains 17 drones** : focused on environmental sensing tasks for early detection of harmful emissions or accumulation of gases in densely populated residential areas. They also measure air temperature and quality to protect visitors [Ayyash et al., 2022]. This organizational structure is connected to a highly reliable communication network (mm Wave/5G). It is managed via intelligent distribution algorithms that adopt the real-time event adaptation model (Real-time Reallocation). These algorithms ensure a response of no more than 20 seconds and coverage exceeding 99.8% of the target perimeter.

The number and type of drones are assigned to each gate based on three main factors:

- Expected maximum.
- human density (PMAX).
- Geographical area of the portal (S).
- Degree of security sensitivity (Lsec).

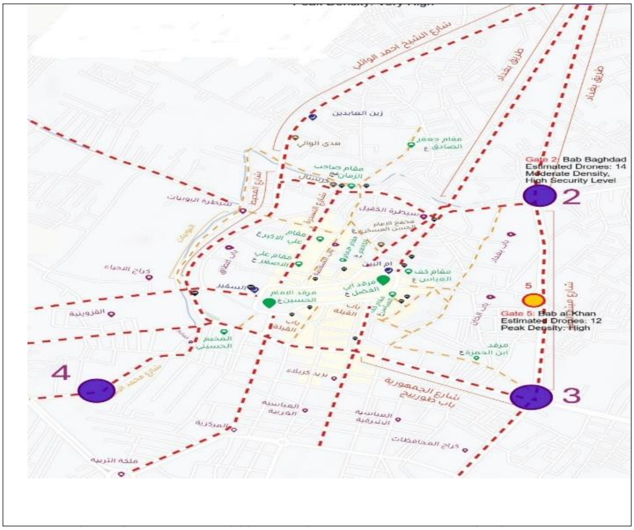

Figure 2. Circular paths for patrolling drones around the entrances of the city and connecting them to the main checkpoint

For this, the following equation was applied to determine the final number of drones for each gate:

$$N_d = \frac{\rho.A}{\mu.C}$$

Where:

N_d The number of tubers required for the gate. ηExpected human density (visitors/m² /m²) .

A: The geographical coverage area of the gate perimeter.

η: single drone coverage efficiency (applicable coverage ratio).

C: The correction factor depends on the threat level and security significance.

Using this model on real scenarios from the previous forty visiting seasons, the need for between 8 and 10 drones per gate was calculated, distributed as follows:

5 optical/thermal monitoring drones.

2-3 chemical/acoustic sensor drones.

1-2 communication drones (Relay Drones).

This estimate has been validated using experimental data within the MATLAB environment, based on simulations of visitor waves, target distribution, and response time requirements under realistic operational conditions (Nguyen et al., 2021) . The final number and type of drones are assigned to each gate based on three main factors:

- Expected maximum human density (PMAX)

- Geographical area of the portal (S)

- Degree of security sensitivity (Lsec)

For this, the following equation was applied to calculate the final number of drones:

$$\boldsymbol{N_{d\,final} = \alpha_{gate} . N_d}$$

$\boldsymbol{N_d}$ estimated initial number. A qualitative significance coefficient derived from a multi-criteria assessment, according to a methodology similar to that adopted in the studies (Ayyash et al. (2022)

4. Estimated Drones Equation :

The proposed system has developed an estimated mathematical model to calculate the optimal number of drones needed to cover each observation area in a crowd environment based on the place's characteristics and actual environmental conditions. The model is based on a simplified linear allocation algorithm considering five basic field inputs, as shown in Table 3.

Table 3. Input equation (5) to estimate the number of smart drones in the control area.

The symbol	variable	Description
A	Area	Geographical area covered (km2)
F	Peak Flow	Maximum Human Flow (thousand people/hour)
S	Security Index	Security indicator (from 1 to 10)
T	Temperature	Temperature (°C)
D	Dust Level	Dust level (from 1 to 5)

The number assigned to innovative drones is calculated using the following relation:

$$\mathit{Estimated\ Drones} = \alpha A + \beta F + \gamma(10 - S) + \delta T + \epsilon D \qquad (3)$$

Where:

α, β, γ, δ, ε are weighted coefficients initially adjusted based on field experiments and modeling within Simulink.

Equation 3 was derived using multivariate linear models, as recommended in the modern literature on the distribution of tasks in drone squadrons under variable environmental constraints (Gonzalez et al., 2021).

3. Integrated spatial and functional modeling of an innovative drone system within a Simulink environment

The modeling of the proposed system is based on three-axis realistic simulations that include:

1. Spatial modeling of the geographical locations of the Gates and Inspection Center.
2. Dynamic modeling of Air Patrol traffic
3. Quantitative modeling of the distribution of drones according to analytical equations

A. Equivalent spatial distribution of biogates

The city of Karbala was represented as a matrix with two-dimensional coordinates, where the main inspection center was centered at the coordinate (0,0), and four main gates were distributed at the four cardinal points representing the four directions (north, south, east, west). As shown in Figure 3, each gate is surrounded by a circular flight path with a radius of 1 km, representing the path followed by drones within periodic monitoring tasks.

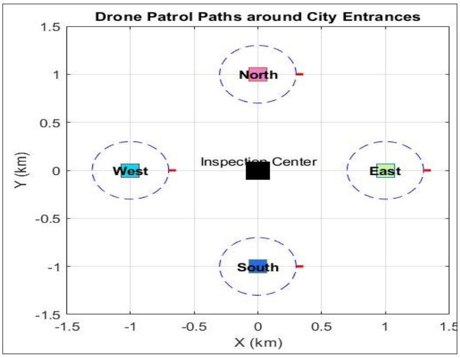

Figure 3. The spatial model of the air patrol routes of drones around the entrances to the city and their connection with the primary Inspection Center.

B. Modeling of the threat level assessment module on board the drone

The proposed system was implemented using the Simulink environment within MATLAB R2024a. The model proposed in this study was based on a multi-path contextual analysis methodology. An integrated modular Architecture (Modular Architecture) has been designed for the mobile intelligent sensing system on drones, as shown in Figure 4. The model consists of four main functional stages that work harmoniously within the Simulink environment:

First: sensor Acquisition module.

- This module includes four categories of specialized sensors:
- Chemical sensor (Chemical Sensor)
- Spectrometer sensor (Spectrometer Sensor)
- Thermal sensor (Thermal Sensor)
- Radio frequency sensor (RF Sensor) Raw signals are sent directly to the initialization and pre-analysis stage.
- GPS module for location determination.

Each signal is routed to its processor (such as Chemical_Processor), and the relevant features are extracted in real time. The Data_Fusion module integrates these readings into a local AI system to generate two outputs:

- Threat level: environmental threat level assessment
- gps_out: geographic location associated with the threat.

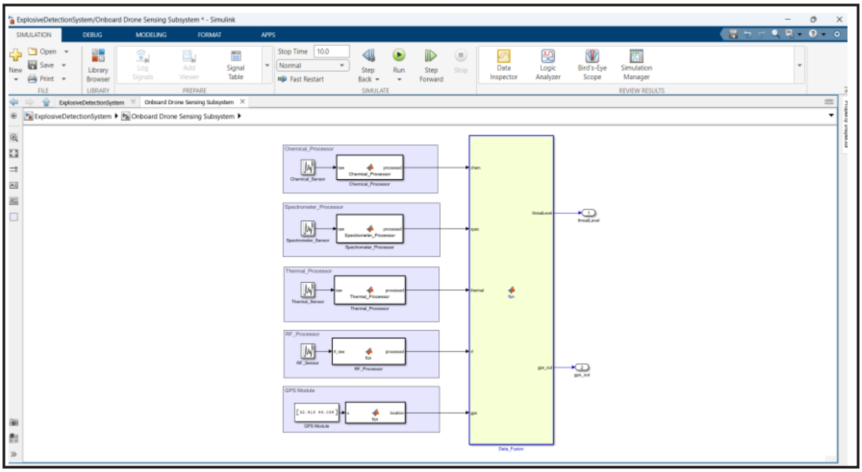

Figure 4. The intelligent sensor module on board the drone integrates data and estimates the threat level and geographical location.

Second: signal processing and feature extraction (Signal Conditioning and Feature Extraction) are used. For each sensor, there is an independent processing unit designed using MATLAB Function blocks, where:

Noise reduction, Extraction of practical features such as absorption spectrum, relative temperature, anomaly frequencies, converting signals into modular representations that can be combined later

$$f_{space}(raw_{spes}) = \text{processed}_{spes}\ , f_{chem}(raw_{chem}) = \text{processed}_{chem}$$

Third: Data Fusion Core :

The Data Fusion Core represents the analytical core of the proposed system within the Simulink environment, in which the processed signals coming from the four different onboard sensors are integrated, namely: chemical sensor (chem), spectral (spes), thermal (thermal), and radio frequency (Rf). These signals are passed to a central merge function that operates in real time, as mathematically defined by the following relation:

$$F_{fusion}(chem, spes, thermal, rf) = \text{theartlevel}$$

This function is implemented using a multivariate weighted merge algorithm or a trained neural network model (such as MLP or GRU) based on available data and the required response time. This function produces a unified threat-level hazard indicator whose value ranges from 0 (safe) to 1 (critical Hazard). It is subsequently used for rapid decision-making at the aircraft or network level. Recent studies have shown (Ahmed et al., 2022) that including edge-level multi-sensor integration algorithms improves accuracy, reduces false alarm rates, and speeds up network transmission time.

Fourth: Alert Broadcasting and Logging Unit

The broadcast and recording module are activated when the threat level exceeds a critical threshold (0.7). This module represents the final stage in the system's intelligent interaction chain. This module consists of two main functional paths:

The real-time broadcast channel (send_log) sends immediate alerts to the command center or nearby control units via audio signals or wireless messages using modern protocols such as 5G or LoRaWAN networks, ensuring rapid response and wide-area coverage. The real-time recording channel (lat_log) automatically documents all detected events in internal logs or cloud databases, including the event time, geographic coordinates, threat type, and aircraft ID. This dual system represents the link between local decision-making and central documentation. Figure 5 shows the detailed structure of this module. The threat core connects to the alarm transmission module, and data is broadcast and recorded in real time, enhancing the system's ability to respond quickly and analyze future events. Recent literature (Ahmed et al., 2022) has shown that integrating smart broadcasting and automatic recording functions within drone-based systems increases response effectiveness and provides accurate analytical archiving to support later strategic decisions.

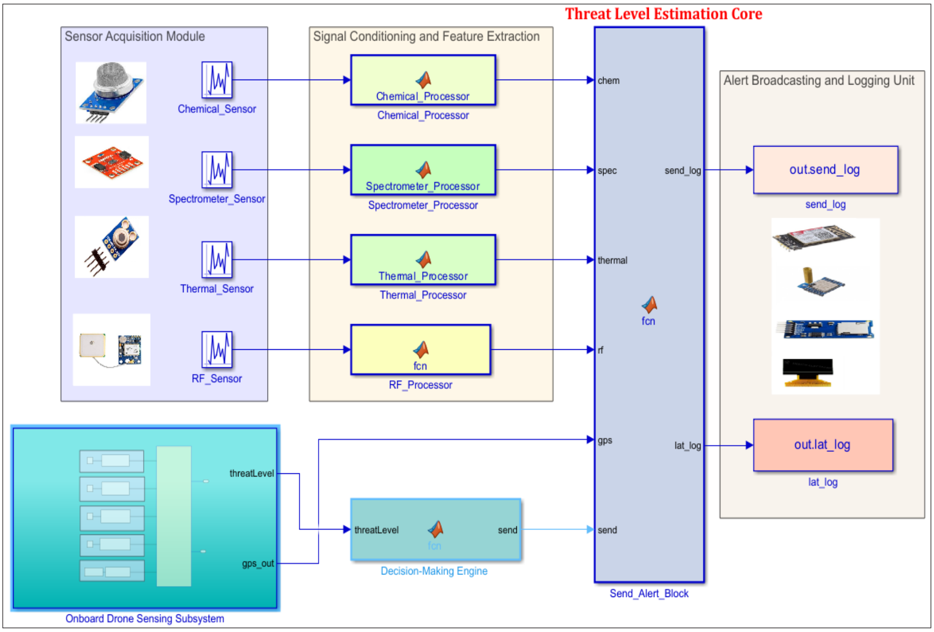

Figure 5. The proposed Simulink system's complete functional structure explains the data acquisition module, signal processing, threat level estimation kernel, decision engine, and broadcast and Recording Module.

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Results and Discussion

This section aims to analyze the performance of the proposed intelligent crowd management system using drones by integrating the theoretical aspect (equations and modeling), the practical aspect (ground-based electronic model), and the results extracted from the analysis of real behavioral data of crowds.

A. Analysis of the impact of environmental variables on the allocation of the number of drones.

Mathematical equation No. (3) has been programmed within an innovative interactive interface developed using the App Designer environment in the MATLAB program, to facilitate allocating the number of smart aircraft according to field environmental variables. This interface allows the user to enter the values for: covered area (A), peak Human Flow (F), safety indicator (S), temperature (T), and dust level (D), both manually and through automatic reading from connected sensors or imported files.

The interface consists of:

1. Numerical Edit fields: assigned to each input variable in the equation.

2. Calculate Button: runs the calculation script and applies the equation immediately.

3. Digital output indicator (Numeric Display): directly displays the output, which is the number of drones allocated in real time.

This interface has been fully integrated into the model's overall structure, designed in Simulink, so the interactive allocation module acts as a complementary component to the resource management module, as shown in Figure 6 in the results and discussion section. Integrating the mathematical model and the graphical interface reflects an engineering approach to developing deployable AI systems. It achieves high operational flexibility that enables the researcher and the user to conduct simulations of various situations efficiently and reliably, even in environments not subject to field flight. Figure 6 shows how the temperature rise to 45°C affected the number of allocated drones, which decreased from 15 to 13 aircraft compared to the standard case (temperature of 40°C). This reflects the system's ability to automatically redistribute and avoid overconsumption of resources within extremely hot environments.

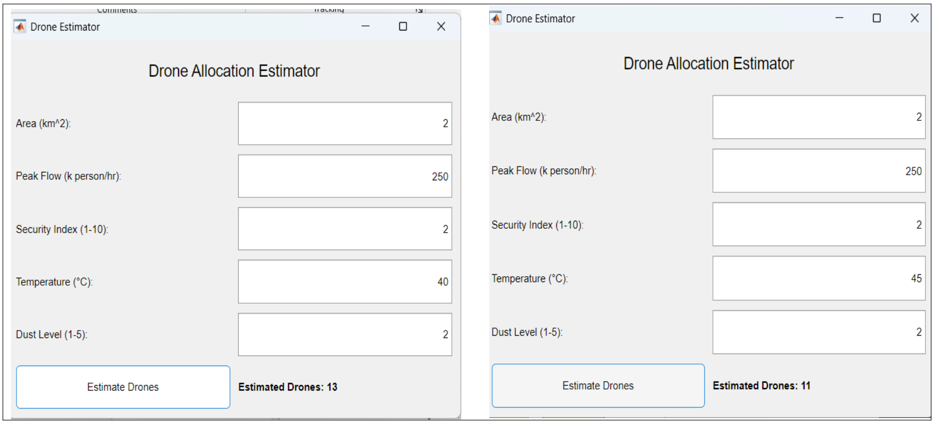

Figure 6. A comparison of two environmental situations using the Intelligent Aircraft number estimation interface shows that an increase in temperature from 40°C to 45°C reduced the number of proposed aircraft from 13 to 11, according to Equation (3).

Figure 6 shows the Daily time flow curves at the four main gates of Karbala: Baghdad, Tuwayrij, Hilla, and Najaf. The critical peak appears at all gates around 12:00 p.m., with the highest flow at the Baghdad gate (>10 thousand visitors/hour), indicating the importance of early intervention at these points.

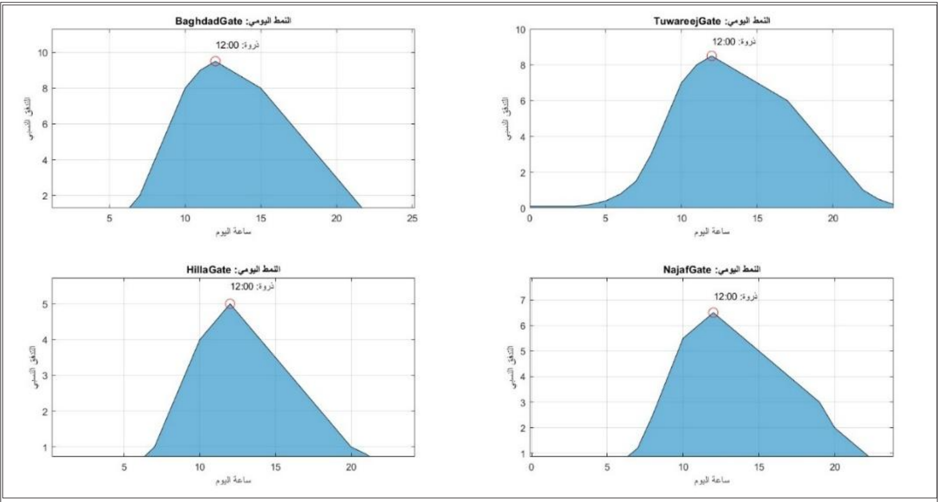

Figure 7. Daily chronological pattern of crowd flow at four main gates (Baghdad Gate, Tuwereej Gate, Hilla Gate, Najaf Gate).

Figure 7 shows the acceleration of the annual peak growth between the years 2019-2024, especially after the 2020 pandemic, as the data showed a sharp increase in the number of visitors. These results feed the aircraft allocation algorithms within the proposed system.

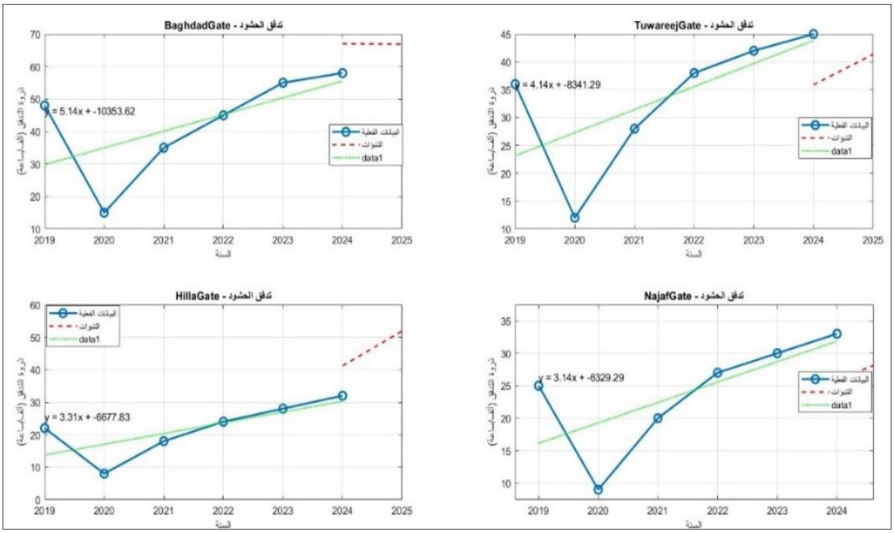

Figure 8. The chronological trend of the annual peak of crowds at each main gate.

The heat map in Figure 9 shows the geographical distribution of the density of visitors in Karbala in 2024. The highest densities are concentrated at the intersection of Baghdad Gate and Hill Gate, which suggests the concentration of aircraft at this point.

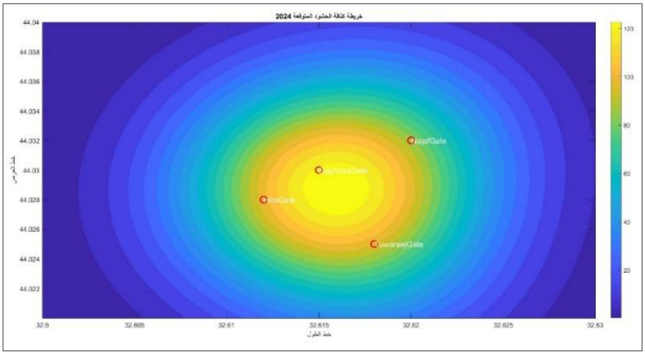

Figure 9. A heat map showing the expected density of crowds in Karbala.

A statistical analysis using Pearson Correlation Coefficient (Pearson Correlation Coefficient) was conducted on the crowd flow data at four main gates in Karbala, namely Baghdad Gate, Tuwereej Gate, Hilla Gate, and Najaf Gate, to understand the temporal and quantitative relationship between the different entry patterns. As Figure 10 shows, the resulting values show a robust correlation between the Tuwereej Gate and Najaf Gate portals, with a value of r = 0.9981 r=0.9981, followed by the relationship between Najaf Gate and Hill Gate with a value of r = 0.9947 r=0.9947. In contrast, the lowest correlation appeared between Tuwereej Gate and Hill Gate (r = 0.9868 r=0.9868), which is still in the range of the statistically high relationship.

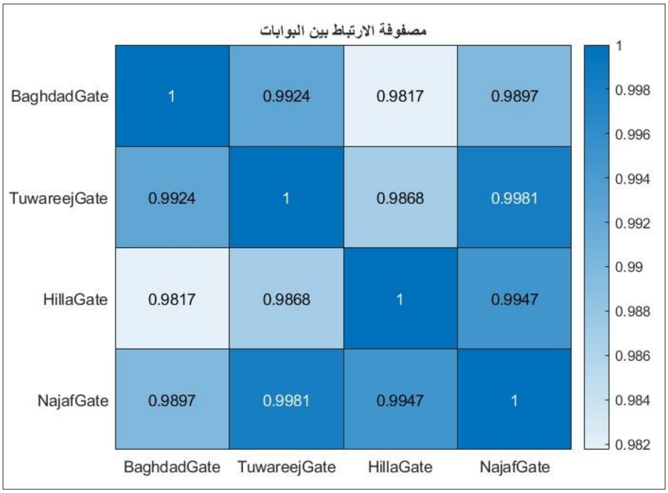

Figure 10. The correlation coefficient Matrix (Pearson Correlation) between the Daily crowd flows at the Baghdad Gate, Tureej Gate, Hilla Gate, and Najaf Gate, and the strong relationship between Tureej and Najaf (r = 0.9981) demonstrates a typical behavioral pattern that can be invested in aircraft resource management.

The results obtained from analyzing the time density curves indicate explicit synchronization at the peak of the Human Flow at Noon at all the main gates of Karbala, which necessitates the design of a flexible, intelligent system to manage the dynamic distribution of drones (UAVs) based on real-time density updates. This time synchronization underscores the importance of integrating ground monitoring systems with smart aircraft to ensure that support is directed promptly and effectively. Moreover, the disparity of peak levels between the gates (Baghdad and Tuwayrij Gates have the highest densities) highlights the need to adopt a predictive model based on priority and gradualness in the geographical distribution of air resources, to ensure that proactive support is directed to the busiest Gates and relieve pressure from them before reaching the danger level.

Finally, the results confirm the effectiveness of the proposed model in anticipating the identification of critical points and highlight the essential role of artificial intelligence and edge Computing technologies in enhancing response speed and reducing the likelihood of human suffocation, especially during peak times at major religious gatherings, such as the visit of forty.

B. Practical verification of electronic integration of the ground model

A ground-based prototype of a smart drone equipped with an Arduino Uno controller was developed during the practical verification phase. A set of environmental sensors was installed on it, including a gas sensor (MQ135), a heat sensor, a GPS module, and communication models. The circuit has been designed to simulate the connections adopted in the theoretical model built in the Simulink environment. Figure 11 shows the electronic system's initial installation, with the components installed on the airframe before commissioning. Figure 12 shows the start of the system's operation, as the optical indicators were lit after the system was fed with power via the USB port, indicating the processing unit's successful operation and readiness to read sensory values and send them to the decision-making unit.

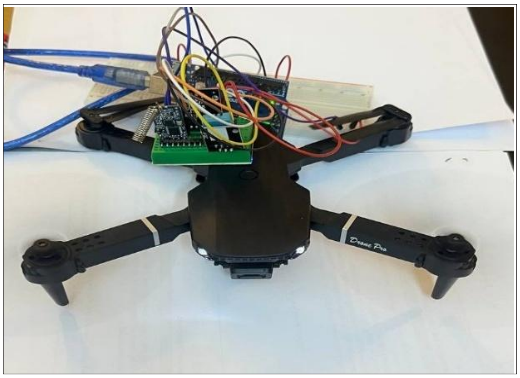

Figure .11 Complete installation of electronic components above the smart plane before Operation.

Form 12. the moment of the electronic form's activation and the system's start.

Although air testing is not currently allowed, this ground-based practical verification enhances the credibility of the design. It demonstrates the integration of the software aspect with the physical components, paving the way for future field tests in a real environment when deregulation occurs. Table 2 shows the results of a ground simulation using an Arduino Uno module for five different environmental scenarios. The impact of environmental variables such as temperature, gas concentration, dust level, and Safety Index on the threat_level hazard index and the number of proposed aircraft was measured according to Equation (5). The results demonstrate a direct relationship between environmental degradation and a higher threat level, reflecting the model's efficiency in dynamic response.

Table.4 The results of the experimental ground verification of the electronic model, showing the relationship between environmental variables, Threat Index threat_level, and the number of proposed aircraft

Status	**Temperature (°C)**	**Gas concentration (ppm)**	**Dust level**	**Security indicator**	**The expected number of drones (according to Equation 3)**	**threat level (estimated)**
1	28	150	1	8	7	0.21
2	30	220	2	6	9	0.38
3	32	300	3	5	11	0.52
4	35	410	4	3	13	0.69
5	38	500	5	2	15	0.84

Conclusion

This research presented an integrated intelligent crowd management model using drones, combining mathematical modeling within Simulink, a dynamic estimation module for resource allocation, and ground-based operational verification using the Arduino system under the constraints of aerial tests. The simulation results showed a clear correspondence with the performance of the actual model, which enhances its reliability and readiness for field deployment. The research contribution is to develop a low-cost predictive framework that aligns intelligent aircraft customization with real-time environmental response, while offering a flexible architecture feasible in sensitive environments such as religious visits and major festivals. The proposed model is one of the first solutions that integrates modeling and practical measurement within an integrated system that automatically responds to changing traffic conditions.

Future work: Upcoming research is focused on testing the model in an actual flight environment and enhancing its capabilities using collective intelligence and machine learning algorithms to improve customization and forecasting. An intelligent control panel to display alerts in real time is also proposed.

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