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Letter to the Editor

A Framework for Intelligent Fire Detection and Evacuation System

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Dear Editor,

Fire incidents in large buildings pose challenges for occupants and first responders. Occupants need to find safe evacuation routes while first responders need to maneuver their way into the building. Fire conditions can become uncontrollable without warning to those located in remote sections of the building. Application of Artificial Intelligence (AI) could help guide occupants to safe evacuation routes and first responders into the building. Here, we propose an integrated trained AI and data collection system that can make short-term predictions on fire behaviour, structural integrity and optimal egress path(s). The system can distribute guidance to users via mobile devices or public address systems.

Several studies have explored intelligent evacuation guidance systems consisting of various sub-components such as fire detection, monitoring building conditions, locating occupants, crowd management and guiding evacuation routes [1–3]. A notable example is the "Understanding Data through Reasoning, Extraction, and sYnthesis (AUDREY)" system [4]. AUDREY utilizes the concept of Artificial General Intelligence (AGI) to provide a Human Like Reasoning (HLR) to extract useful information from sensors and provide it to firefighters on a head up display.

Artificial Neural Networks (ANN) have been used to predict wildfires as well as compartment fires. Researchers relied on zone models and Computational Fluid

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Dynamics (CFD) to generate training data on fire dynamics [5, 6]. Structurally, Machine Learning (ML), genetic algorithm and gene expression programming have been used to predict capacities of structural elements [7, 8].

Most real-time evacuation systems [1–3] rely on a pre-populated database of fire scenarios. However, real-time fire behaviour could be different. Hence, an AI based system is proposed to provide short-term prediction of fire behaviour faster than real-time during a fire incident. The system guides occupants and first responders in and out of a building under fire. The system comprises the following components:

1. Detection
2. Fire Dynamics
3. Structural Response
4. Evacuation Navigation and Routing and
5. AI Emergency Management and Decision Support

The *Detection* component gathers spatial and temporal data from fire propagation sensors, structure health sensors and population sensors. The *Fire Dynamics* component is trained to predict fire growth, smoke movement and fire decay. The *Structural Response* component is trained to predict structure behaviour in fire based on data from structure health sensors. The *Evacuation Navigation and Routing* component finds optimal evacuation routes based on input from the other components and an embedded representation of evacuee response. The *AI Management and Decision Support* system combines results from all other components and convey directions to occupants and first responders through a smart handheld device. Figure 1 illustrates the relationship between the different system components.

1. Detection

During operation, the AI system receives information from three types of detectors/sensors: fire propagation sensors, structure health sensors and population sensors.

Fire Propagation Sensors Smart fire detectors such as gas analysers, smoke, CO, temperature and IR sensors are connected to a common network. As fire progresses through its phases (ignition, smoldering, growth and propagation), fire detectors are triggered at respective phases depending on their proximity to the ignition source. Input data to the AI system are spatial and temporal distribution of different fire related measurements. Thus, the trained AI system can identify location of the fire, what is burning, rate of fire growth and direction(s) of fire propagation.

Population sensors: Approaches to record movement of occupants in and around a building include technologies such as CCTV, footpads, passive or active detectors, WIFI/Bluetooth/GPS counts and dedicated people sensors (infrared, beam, LIDAR, etc.). Given the connectivity of population sensors to a common

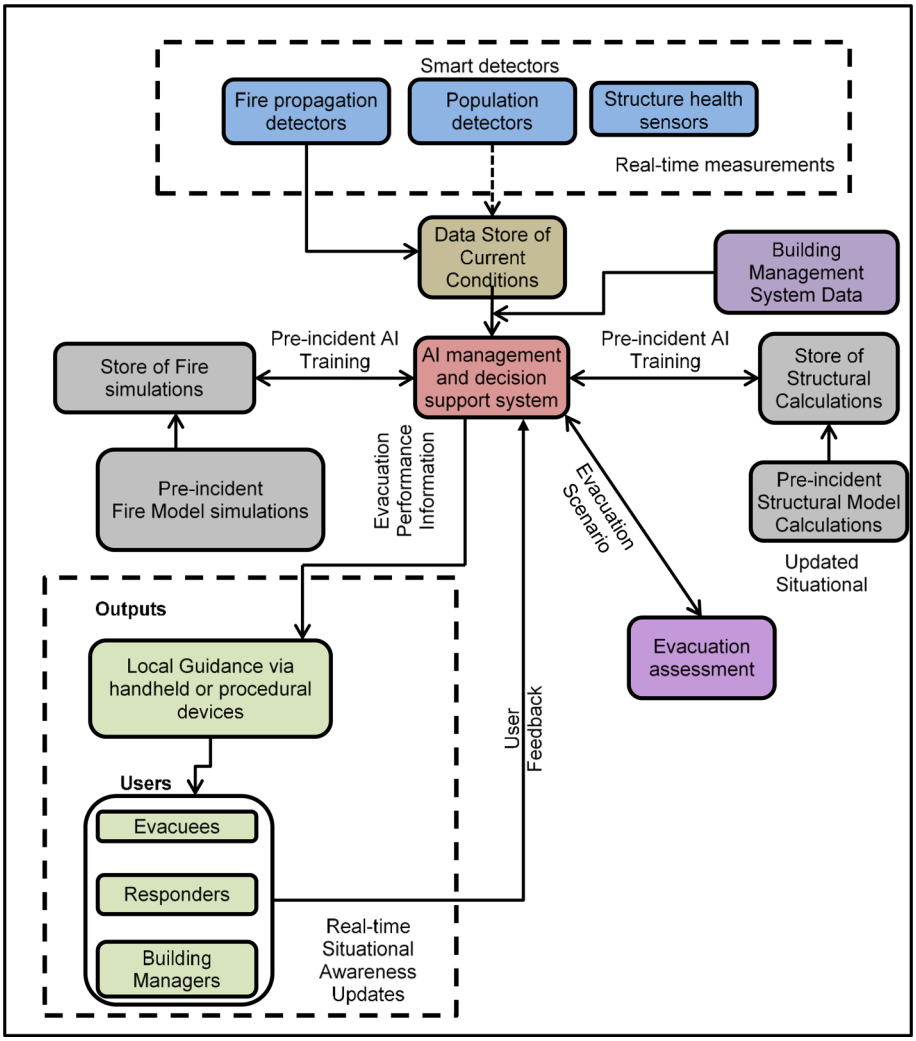

Figure 1. Relationship between different system components.

network, spatial and temporal distribution of occupants are available to the AI system. In addition to the spatial and temporal distribution of fire related measurements, the trained AI system returns optimal evacuation paths for individual occupants.

Structural Health Sensors Structural health sensors such as thermocouples, strain gauges and fibre optics are used to gather information regarding thermal and structural load conditions. Data gathered are the main input to the structure health AI component which predicts information on the structural integrity and conveys it to first responders.

2. Fire Dynamics

Predictions of fire behaviour in two connected compartments, using ANN, were extended to predict fire behaviour in multi-compartments [8]. Because of the cost prohibitive aspect of generating large data set from experiments, CFD and zone models such as CFAST are commonly used to develop data bases of fire dynamics related parameters sensors to train ANNs [6].

In the proposed framework, CFD provide data needed to train an AI system. Results include detailed information about fire propagation and rate of spread. Sensors are also simulated in the domain. The sensor readings as well as the inputs and outputs of the simulations are used to train the AI system. The system is trained to detect the initial fire location, initial burning material, fire growth rate coefficients, smoke movement, onset of flashover, Heat Release Rate (HRR) of ventilation controlled fires, duration of the fully developed phase and approximate profiles of fire decay period. Depending on the type of input sensor data and desired output data, different AI algorithms are employed. For example, for image and/or video input, convolutional neural nets (CNNs) are deemed appropriate. For more conventional sensors with time series measurements, long-short-term-memory models have shown promising results in fluids modeling and fire detection in tunnels [9]. For short-time predictions of HRR and temperature, feed forward networks have proven successful [6]. Physics-informed-neural-networks (PINNs) are applied to speed up the training process [10]. In PINNs, physics based correlations are applied as part of the loss function. For example, equations such as the "t-squared" fire growth equation, can be used to guide the training results to the outputs faster, reducing the amount of data required to train the AI without losing generalizability.

3. Structural Response

The main role of the structural response element is to determine the damage level to the structure due to the fire and determine the probability of local and global failure in the structure in real time. Previous incidents point out the importance of predicting local failure and global progressive collapse of the structure. For instance, in the World Trade Center collapse, first responders were trapped partly due to egress routes being obstructed due to structural failure [11].

There are three key inputs needed for predicting the structure's behaviour,

- Information regarding the structure (system and components)
- Pre and post incident loading conditions
- Local and global damage levels

Once this information is gathered, coupled fire-structure simulations can predict the behaviour of the structure. In order to provide real-time results, the structural-fire model then trains an AI component to predict the structures behaviour in real time.

This structure failure prediction system has the following components: sensor network, structural model, damage detection component, and AI.

A multiscale/sub-structuring approach is needed to capture the structure's behaviour at different scales. The structural model then is used to simulate various probable scenarios and to compile a repository of pre-run incident scenarios. This repository is used to extract simulated sensor data to train the AI system. Damage detection component uses the modeling data to detect local and global damage levels. The final result comprises a measure/index of safety for various locations in the building. To achieve best predictions, the trained AI system could be used to optimize the sensor network topology and components.

4. Evacuation Navigation and Routing

The proposed navigation and routing system comprises an evacuation assessment and a local guidance component. The **evacuation assessment component** assesses evacuation routes given the current conditions to rank viable candidate routes. At the core of this component is an evacuation model that contains a library of pre-simulated evacuation scenarios. The AI system then scans this library to determine a match with the current sensed conditions. If there is a match, the system selects this scenario to provide output from the existing simulation results associated with this scenario. If there is no match, a new real-time evacuation model is run to generate more representative information. The main output of evacuation assessment component is an optimal evacuation route for populated compartments.

The local guidance component takes the output from the AI management and decision support system and translates it into guidance that can be displayed to three different user groups. This includes route selection, timing of movement and objective (goal location). The information can be displayed on mobile devices, public address systems, or other display technology depending on the user group (managers, responders and evacuees), the type of scenario being faced (real or planning/training) and their responsibilities at that time.

All user groups can provide feedback/input to the system. For instance, firefighters may indicate the staircase they will use for ingress and label it not available for occupant egress (or at reduced capacity), prior to their arrival. This provision can act as a corrective to the simulated data and also allow users to test hypothetical scenarios under non-emergency scenarios (e.g. in a training mode). Details of the navigation and routing system are shown in Fig. 2.

5. AI Emergency Management and Decision Support

At the core of the outlined framework is an AI system that is trained using previously simulated fire and evacuation scenarios. During a live fire situation it collects data from the sensors related to fire dynamics, structural response, and occupants' locations. Relying on the previously trained models, short-term forecasts are created. From these forecasts, the emergency management component maintains an envelope of habitable spaces that separates the areas of the building

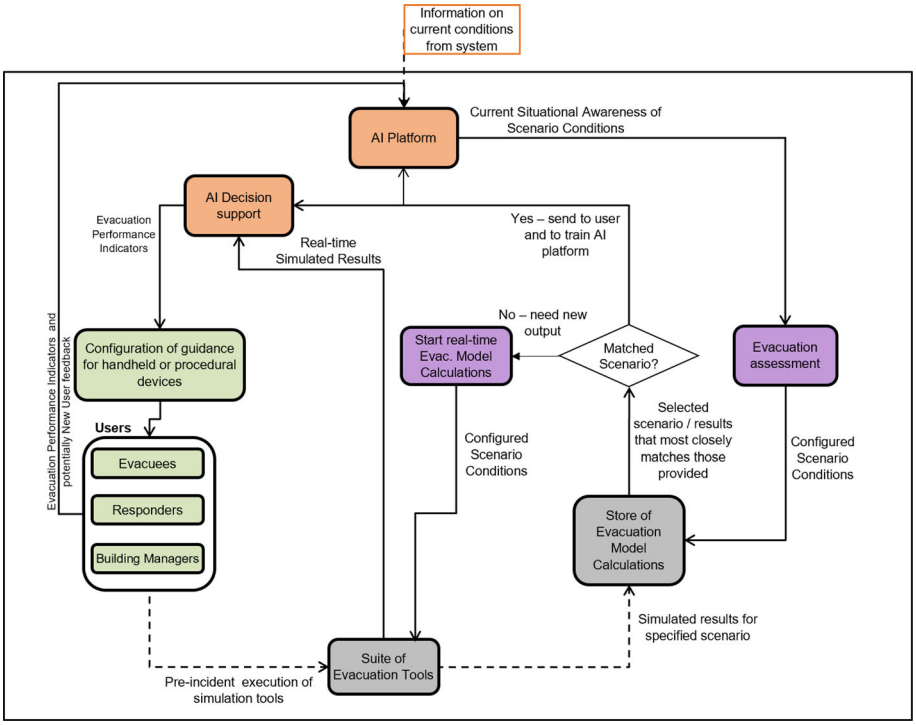

Figure 2. Evacuation navigation and routing system and its components.

that are available/tenable from those that are unavailable/untenable. Boundaries of the habitable envelope depend on factors such as visibility, toxicity, temperature and structural integrity. The AI system maintains an envelope for each factor where its level is below a predetermined threshold. The "overall" habitable envelope is the intersection of all envelopes from all factors. The envelope's boundaries shall be time dependent and can be forecast to a hypothetical future point in time, based on input from the detection component. The future habitable envelop informs the Evacuation Navigation and Routing component on the feasibility of advice given for evacuation and entrance routes for first responders.

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