An Autoregressive Exogenous Neural Network to Model Fire Behavior via a Naïve Bayes Filter

SYED ADNAN YUSUF, ABDULRAHMAN A. ALSHDADI, RAYED ALGHAMDI, MADINI O. ALASSAFI, AND DAVID J. GARRITY

1Research and Innovation Department, ELM, Riyadh 12382, Saudi Arabia
2Department of Information Systems and Technology, College of Computer Science and Engineering, University of Jeddah, Jeddah 21577, Saudi Arabia
3Department of Information Technology, Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah 80221, Saudi Arabia
4STS Defence Ltd., Gosport PO12 1AF, U.K.

Corresponding author: Rayed AlGhamdi (raalghamdi8@kau.edu.sa)

This work was supported by the Deanship of Scientific Research (DSR), King Abdulaziz University, Jeddah, under Grant DF-137-611-1441.

ABSTRACT This work presents an artificial neural network-based linearly regressive technique for the prediction of a temperature rise event caused by a fire in enclosed building environments. The method predicts temperature range in a burning compartment based on the historic fire behavior data modelled via a neural network algorithm. The approach further extends the method by transforming the regression outcome as actionable information for firefighters via a self-organising feature map (SOM) fire-stage-clustering algorithm which categorises the predicted temperature range to provide warnings of any imminent and catastrophic temperature variations. The methodology implements a linear regression artificial neural model to model and predicts catastrophic temperature variations that are a threat to fire-and-rescue personnel in enclosed burning compartments via a ceiling gas-layer temperature acting as an exogenous variable. Based on the predicted temperature window, the SOM classifier maps the output in distinct clusters while isolating spurious prediction spikes and categorising the output to various self-organising threat/warning levels. The model was trained on temperature data captured with pole-mounted sensors in controlled fire training exercises. Tests carried out in actual fire-settings showed the capability of the SOM classifier to generate evacuation warnings for forecasted temperatures exceeding 300 °C in 5 - 30 seconds ahead of the occurrences. Tests on these short-term and long-term prediction ranged from 78.31% to 96.27% in accuracy whereas the SOM classifier generated an overall accuracy of 76.92% to 100%. The techniques also showed a high resilience against both false-positives and false-negatives.

INDEX TERMS Artificial neural networks, fire behaviour modelling, linear regression, self-organising feature maps.

I. INTRODUCTION

The understanding of uncontrolled fire dynamics in enclosed human environments is of immense importance for a wide range of domains including personnel safety in emergency rescue services, fire alarms, industrial automation and robotics. A better assessment of fire behaviour in an indoor environment is particularly important for first-responders such as firefighters who need to rapidly assess the situation and respond accordingly [1]. Personal safety is at foremost for firefighters attending a fire in a rapidly developing situation.

The associate editor coordinating the review of this manuscript and approving it for publication was Weipeng Jing.

Personal Protective Equipment (PPE) for firefighters can only withstand temperatures that are lower than 300 °C whereas temperatures during a fire can often exceed 500 °C during short periods that prove fatal for anyone present in that compartment. For temperatures exceeding 300 °C, charring of PPE begins and with the accumulation of hot gases, material types present and level of ventilation, the temperatures may rapidly rise to 500+ °C in a duration that may be as low as half a minute due to the abundance of combustible materials in modern buildings[1]. The measure of uncertainty of fire behaviour in these circumstances makes survival very difficult for any human beings present in that compartment. Since the rate of temperature increase in urban fires can be highly
nonlinear and unpredictable, especially in enclosed spaces with a variety of fuel types such as furniture, claddings, stored goods, as well as the building construction material, indoor fire behaviour is known to show a high level of uncertainty which is very challenging to predict merely by human observation and experience.

Based on the existing safety framework for firefighters and the lack of intelligent sensing mechanisms to report abrupt temperature changes, this work presents an intelligent approach to predict the rapid rate of temperature (ROT) rise events in typical fire compartments in built environments. This is achieved in the presented research by leveraging the generalisation ability of temporal artificial neural networks (ANN) to develop a temperature forecasting and categorisation system.

Self-organising maps (SOM) is one of the most widely used neural network architectures used for clustering. The architecture has a set of neurons that form a rectangular topological grid. Any pattern presented to a SOM results in the neuron with the closest weight vector to be considered a winner. This also leads to the weights of the neighbouring neurons to be adapted. The process creates an automated pattern clustering technique that finds many uses including unsupervised learning of patterns in datasets that are hard to label and hence provides the rationale in the proposed methodology. The mechanism utilises a supporting variable, which is the ceiling gas layer temperature, to further improve on the ANN as a non-linear autoregressive model with an exogenous variable (NARX) model. The regression outcome of this stage is then mapped and clustered via a self-organising feature maps (SOM) classifier to assist with the elimination of false positives (FPs) and negatives (FNs) and categorise the output into distinct, human-readable categories.

The work presented in this paper is organised as follows: Section II presents a background overview of compartmental fire behaviour, and existing machine learning techniques reported in the literature. Section III presents the architectural design and methodology of the proposed system and Section IV provides details of the experimental setup and results obtained.

II. BACKGROUND & RELATED WORK

In enclosed burning environments, temperatures increase at a faster rate at ceilings than at the levels closer to the floor due to hot air moving upwards. The temperature increase hence follows a top-to-bottom movement pattern was burning with gases moving downwards towards the floor. This forms a high-temperature-blanket that moves downwards as the temperature increases. The boundary between this downward movement of hot gases and cooler air below is termed as the ‘neutral plane’, the height of which plays a critical role in the spontaneous ignition and subsequent, catastrophic increase of temperature within that compartment (III). As the burning continues, this higher-temperature neutral plane moves from the ceiling to floor which, subjecting to the available air and fuel, eventually results in a sudden and simultaneous ignition of any combustible materials in the room. The phenomenon is called “flashover” which is regarded as the stage where it becomes impossible to evacuate anyone present within. At this stage, the rate of temperature is generally reported beyond 300+ °C which leads to a rapid spread of the fire to the elements that are in not even in direct contact with fire [2]. In fire rescue missions, this leaves little or no time for any personnel within that space to escape unharmed [1]. Unfortunately, firefighters are often unaware of this temperature change due to the same PPE they wear for their safety.

To gain a better understanding of enclosed, residential fires and ascertain the exact cause of loss of life in fire rescue exercises, the National Institute of Standards and Technology (NIST) investigated two separate incidents [3]. On 30th July 2002, a training exercise resulted in the loss of two firefighters in a single-story family home. The drill involved setting-up of a fire-load in and around a bedroom closet. Once it was ascertained that the fire had attained a developing stage, a two-person search and rescue (SAR) team entered the environment followed by two three-member groups of firefighter hose crew. With the developing fire, the smoke increased rapidly and diminished visibility, making it impossible to locate the SAR team. After approximately 3-and-a-half minutes of SAR entry, a flashover occurred with flames seen extending out of the front bedroom window. Since the SAR team was not located at this stage, an evacuation signal was sounded, and the bodies of the SAR team were shortly recovered from the building after the fire was extinguished. An investigation onto the incident eventually discovered uncontrolled ventilation resulting from a fire room window being broken out from outside resulting in ingress of air. This led to rapid creation of combustion conditions with extremely high temperatures within a short duration of time with little time for the firefighters to escape unharmed.

To assess the circumstances leading to flashover in this case, similar conditions were recreated with five different combinations of fuel load and ventilation conditions. Temperature sensors were mounted at three different heights from the ceiling. A window within the fire room was opened at the 240th second allowing an ingress of air that resulted in the previously ventilation-limited fire to reach a flashover within the next 40 seconds. Logged temperature data during these experiments showed the highest sensor reporting flashover earlier in the time since the lowering neutral plane of hot gases moved downwards. All 5 scenarios resulted in a flashover where conditions were beyond what a full PPE was capable of withstanding. From the data, it was understood that with temperatures in excess of 260 °C and heat flux of 20 kW/m², the survival time even in PPE outfit was limited to less than 30 seconds.

In the circumstances discussed above, it was observed that during fire suppression activities, visibility was obscured by thick smoke and hence visual indicators on developing hazards could not be relied upon. Thermal interface cameras (TIC) used to identify various flashover indicators did not provide a prolonged usage due to their bulky nature.
Moreover, personal sensing of temperature variations by firefighters was difficult due to their protective clothing. Hence, any rapid transition of temperature via rollovers or rapid smoke exit indicators only become noticeable when it was too late for a safe exit. Though existing firefighter PPEs are designed for elevated temperatures, they can only withstand such temperatures for a short time duration. However, PPEs do not offer unlimited protection against thermal radiation, hot gas convection and direct contact [4]. While providing protection from the direct thermal effect of fire, the PPE does make it difficult for the firefighters to sense sudden temperature increases due to hot gas convection and thermal radiation. To predict such emergencies, firefighters are trained to assess various cues and indicators to understand fire behaviour. Yet, burning structures are highly unpredictable where a sudden temperature change may occur due to factors the rescue team are unaware of. For instance, a breaking window or collapsing structure may unnoticed allow an influx of air providing extra fuel to the burning materials and hence changing the fire dynamics in the compartment drastically.

Temperature and heat flux have often been used as reliable indicators of understanding the fire spread behaviour. The rate of temperature change in a burning compartment is directly proportional to the amount of heat-flux generated. Initial tests in this domain were undertaken by the Building and Fire Research Laboratory, National Institute of Standards and Technology (NIST) [1]. The objective was to understand the overall temperature change and heat flux behaviour of residential rooms in the presence of fuel and ventilation-controlled fires. During these experiments, various building rooms were subjected to single-run, incipient-to-cooling-phase fire experiments where temperature and heat flux changes were recorded by a set of thermocouples mounted at variable heights. The work done by [1] investigated the ceiling temperature patterns in the presence of “flame-sparks” observed sometime before flashover occurrence. The experiments noted temperatures of 600 °C at a height of about 10mm from the ceiling. In the presence of these hot temperature patterns, the temperatures patterns at human height remained low for extended periods. Babrauskas [5] used this criterion to perform a full-scale 10-mattress test to replicate conditions like a full-scale compartment flashover. The tests also revealed gas temperatures of nearly 600 °C. A further similar analysis by [6] reported an average room temperature increase of about 450 to 650 °C. The test further noted a spontaneous (non-contact) ignition of a crumpled newspaper at floor level shortly after the ceiling temperatures reached 540 ± 40 °C. Additional tests by [7] in mobile homes reported similar newspaper charring when the ceiling temperatures reached a range of 670 to 770 °C. In fires not resulting in a flashover, the ceiling temperatures were still reported to reach 300 – 375 °C. Lee and Breeze reported such ignitions at 650 °C in rooms and 550 °C in doorways of submarine hulls. For non-flashover cases, the temperature in similar circumstances reached 427 and 324 °C. In their work, Budnik and Klein concluded doorway conditions to be more reliable flashover indicators. Moreover, the type of fuel present within compartments played a substantial role in rapid ceiling temperature increase. Vytto and Babrauskas [5] reported tests with fire originating from a urethane foam chair to reach more than 800 °C. Tests by [8] reported average upper room gas temperatures to reach 706 ± 92 °C with a 90% confidence level.

The characteristics and spread behaviour of compartment flashovers have been rigorously researched and are related to various factors including ventilation openings, fuel type and the duration of a burning process [1], [9]–[12]. Moreover, substantial research is being done to understand fire behaviour in urban dwellings in the presence of factors such as construction type, materials present and the fuel type feeding the fire. Once the fire starts in a structure, the temperature field is a critical assessment factor in fire risk analysis. Many techniques report on the use of sensors to monitor firefighters’ health and warn them of any threats to their safety. Several safety areas are being considered including tracking indoor location of first responders [13]–[15], physiological monitoring [16]–[18], and communication [19], [20]. There have also been substantial advancements in the research and development of intelligent threat assessment systems for firefighters. Pavlicek et al. [21] recently proposed a threshold-based heat-transfer model for firefighter PPEs. The proposed system, though capable of calculating heat-flux being transferred to a firefighter’s body, only uses discrete temperature measurements and exponential functions with no feedback from previous heat flux patterns hence making it incapable of predicting fire behaviour. Another work reports on the design and development of a physiological monitoring system capable of withstanding high-temperature levels [22]. Many investigations have however focused on fluid dynamics modelling systems [23]–[25]. Numerical simulations via field model [26], statistical estimation of smoke flow for fire spread behaviour estimation [27] and soft-computing techniques have also been reported for compartment fire prediction [28], [29].

From the detailed analysis of existing temperature/fire-behaviour-related research, it becomes apparent that despite the existence of a detailed research body undertaking investigations in various relevant disciplines, there has been a profound lack of research done via machine-learning techniques to model nonlinear, compartmental fire behaviour. The focus has not yet shifted to the development of a universal, temperature-driven model that can predict temperature changes in compartments in real-time. Hence, in addition to focusing on modelling, the proposed work also explores the utilisation of various environmental factors near first responders to assess their direct contribution to the behaviour of fire. To achieve the objectives of this work, the proposed methodology leverages the generalisation ability of temporal artificial neural networks (ANN) to develop a linear-regression-based temperature forecasting and categorisation system. The former (forecasting) mechanism utilises an exogenous variable to improve the underlying
model’s generalisation which is then mapped onto various fire behaviour prediction stages based on the inter-node clustering capabilities of a SOM classifier to eliminate outliers and categories regression. The latter (SOM classifier), hence implements a warning categorisation system which is more understandable to humans. A detailed system design, architecture and methodology are presented in the next section.

III. FIRE BEHAVIOUR PREDICTION MODEL ARCHITECTURE

The proposed technique evaluates the effectiveness of an exogenously trained autoregressive, time-series neural network (NARX) model to identify nonlinear fire behaviour based on the height of neutral plane hot-layer. The model utilises the “neutral plane” temperature as an exogenous (external) factor in addition to the regular, past rate-of-temperature-change window and utilises a sliding window pattern to predict future temperature anomalies as a warning mechanism to output a future temperature range. The regression outcome is then clustered into a self-organising clustering mechanism to eliminate false positives due to spurious temperature spikes in the NARX classifier based on the inter-node distance of the SOM classifier.

The ROT prediction and categorisation instrument described in this work form its basis on the fire dynamics and behaviour findings and the subsequent observations gathered from fire tests carried out by NIST [1] with the fire behaviour shown in Fig. 2 for two controlled fire suppression exercises:

- Observation 1: Temperature increases at the ground level at a slower rate than ceiling temperatures but generally follow the same characteristic pattern. This depends on the position of the boundary layer of hot combustion gases (neutral plane)
- Observation 2: The rate at which this “neutral plane” lowers to the ground level depends upon a wide range of factors including air ingress as well as the fire source intensity and fuel type available.
- Observation 3: The associated temperature pattern goes through a shoulder-and-head (STH) form where the shoulder stage may/may not remain stable for some time before leading to the head-stage with temperatures exceeding 300+ °C.

The abovementioned readings were observed from the fire dynamics datasets reported in the NIST data and the following characteristics were observed in-room fires [1], see Fig. 2.

The dining room temperature of 201°C recorded at near ceiling height (7.42 ft). At this instance, the temperature at the shoulder height (5.50 ft.) was 146°C. It took about 24 seconds for the shoulder-height temperature sensor to report an increase to 206°C. By this time, the ceiling temperature had already reached 310°C which then gradually increased to 494°C in about 12 seconds thereby resulting in a flashover.

Similar observations were made for the bedroom dataset and the following hypothetical arguments were derived:

- Hypothesis 1: The flashover phenomena were achieved via universally similar STH patterns
- Hypothesis 2: The ROT change patterns in a developing fire formed single to multiple, increasing STH patterns as pre-alarm indicators of an impending flashover
- Hypothesis 3: The ROT increased as a function of the gaseous “neutral plane” which lowered till the flashover stage

The work hence draws its technique from the work reported by [30], [31] in the design of a body-mounted intelligent fire-alarm. The hypothetical arguments presented above are evaluated and addressed via the presented AI technique below.

A. NEUTRAL PLANE AS THE EXOGENOUS VARIABLE FOR TEMPERATURE PATTERN IDENTIFICATION

The method exploits the lowering neutral plain as an exogenous identifier for the proposed time-series neural network-based temperature prediction module. It uses a standard backpropagation ANN classifier trained to model and predict future temperature variations based on the compartment’s previous temperature variation pattern in addition to the height of the neutral plane reported by the higher sensors. The model takes its training inputs in a sliding window pattern as shown in Fig. 3 of any length n mapped to m future values captured by Type-K thermocouples recorded at the heights of 1.68 m and 1.08 m representing human shoulder and waist heights respectively (Fig. 5).

At a given moment t0 in time, the input data for the training model comprises the past N measurements. In the example shown in Fig. 3, N = 10 so the input data comprises of values \( T_{th-9} \) to \( T_{th-0} \) captured by the thermocouple at times \( t_{-10} \) to \( t_{1} \) respectively (where \( t_{1} \) is the time of the most recent capture). The model processes these inputs to calculate \( P \) predicted values for a future window of time, where \( P = 10 \) and so the predicted values comprise of temperatures \( T_{1} \) to \( T_{10} \) corresponding to future times \( t_{1} \) to \( t_{10} \) respectively, recorded at 2 hertz. The value of N was set based on a value and sensor-frequency that provided a sufficient time-duration for the firefighters to vacate the premises. The value also correlated with real-world fire-drills undertaken by various fire services in the US and the UK.

Based on the predicted window of future temperature values, the NB algorithm determines whether these values meet a given condition for triggering a warning or imminent flashover. In the proposed case, the algorithm determines whether a portion of the predicted temperature values from the ANN linear regression outcome exceeds a warning range of 150 to 299 degrees °C to raise a “pre-alarm” condition and exceed the threshold of 300-1000 °C for detecting a flashover “alarm” event.

As time progresses, the sliding past and future windows move on in time as more temperature data is received. Following the calculation shown in Fig. 3, further temperature sensor data is received for time \( t_{1} \), so the next sliding past window of time will correspond to the temperature values captured in times \( t_{-8} \) to \( t_{1} \), and the next future window of time
for which the predictions are made corresponding to times $t_2$ to $t_{11}$. Hence, the calculation is repeated multiple times for each successive window of sensor data to provide ongoing predictions of the risk of temperature rise events.

The proposed ANN and SOM architecture that develops the overall end-to-end early warning pipeline is shown in Fig. 4. It comprises an input layer containing many nodes. Each of the temperature values $T_n$ to $T_{n+s_i}$, with $n$ showing the current starting index of the sliding window, and $s_i$ being the input sliding window size, is fed to a corresponding one of the nodes of the input layer. The network contains only one hidden layer where each node of the hidden layer outputs a value $f(x_0, x_1, \ldots, x_N; w_0, w_1, \ldots, w_N)$ obtained as a function of all the inputs to that node and a corresponding set of weights $w$ learned during the training phase. Separate and random sets of weights are defined during the initialisation phase for each node of the hidden layer as well as each input.

The output of a given node of the hidden layer could be determined per the following equation (1):

$$f(x_0, x_1, \ldots, x_N; w_0, w_1, \ldots, w_N) = \sigma(t)$$

In (1), $t$ is the weighted sum of the inputs to the node:

$$t = \sum_{i=0}^{N} x_i w_i$$

and $\sigma(t)$ is a sigmoid function used as an activation function for controlling the relative extent to which each node of the
hidden layer affects the final prediction:

$$\sigma(t) = \frac{1}{1 + e^{-\beta t}}$$  \hspace{1cm} (3)

In (3), $\beta$ is a slope parameter defined in the model coefficients which could be the same for all nodes or could be set differently and learnt for each node as part of the training phase.

The final layer of the ANN is an output layer comprising several nodes whose outputs represent the predicted temperature values $T_1$ to $T_{10}$. As for the hidden layer, each output node receives the values calculated for each node of the preceding layer and calculates its output as a function of its inputs $x$ and weights $w$ as defined in equations 1 - 3.

### B. CLASSIFYING OUTLYING (FP/FN) OUTPUT AND CATEGORISING FIRE-STAGES IN NARX OUTCOMES VIA A SOM NODE GRID

The time-series outcome from the earlier, ANN stage essentially predicts a future temperature window. The input data used to predict this pattern show a high level of noise due to random spikes occurrences as sensors get close to very hot
surfaces in the compartment. An example of such a characteristic is shown in the regression outcome section of Fig. 4. Such a dataset, if used to train a NARX model, leads to the regression model getting trained on a high-temperature-input to low-temperature-output (or vice-versa) mapping leading to an overfitting model. This generates short-duration, low-temperature outliers in the output range which are either false negatives (FNs) or false positives (FPs). These outliers may occur several times in a single burn period and must be eliminated to predict a stable alarm condition. A semi-supervised SOM model at this stage clusters the output nodes based on their inter-node Euclidean distance. The grid shown in Fig. 4 represents a 2-D node map separating various nodes based on their inter-nodal distance. This is further useful as linear regression outcomes of the NARX model shows a range of temporally defined future temperature values which are not useful for quick human understanding. Hence, additional use of this semi-supervised, clustering classifier is to exploit its ability to cluster linear regression outcomes to a human-readable output by clustering them into groups. Based on the similarity of temperature ranges, the self-organising capability of the SOM layer clusters similar ranges into various groups. As the prediction values are known from the regression layer, a general classification of the layer can be made to belong to a certain group.

The clustered nodes are hence classified based on a ground-truth derived from the NIST Living Room (NIST-LR) and Dining Room (NIST-DR) datasets (Fig. 2), to label each temperature occurrence into three distinct classes as follows:

- Normal: 15 – 150 degrees °C
- Pre-Alarm: 151 – 299 degrees °C
- Flashover imminent: 300 – 725 degrees °C (as per the maximum temperature in NIST-LR/DR datasets)

The SOM training involved in this case utilises data from NIST-LR/DR datasets mapped to the three thresholds explained above. The grid is a 2-D mapping of ANN output nodes where each unit $i$ is represented by a vector $v_{i1}v_{i2} \ldots v_{iD}$ where $D$ is the input vector dimension. Hence, for a 30-second regression outcome covering 15 seconds (at 2 Hz), the grid dimension would be $30 \times 30$. These units are connected to the adjacent ones via a neighbourhood relationship which in the proposed case is the inter-neuron distance. During the training, SOM forms an elastic net folding onto the cluster formed by the generated regression outcome. In the existing case, the inter-neuron distance isolates distinct temperature ranges similar to the NIST patterns shown in Fig. 2. Moreover, any abrupt prediction spikes that may lead to false negatives, and in more serious cases, false negatives, would be isolated as outliers due to a higher inter-neuron distance. The underlying rationale here is to minimise false alarms while automating the overall warning process.

### IV. EXPERIMENTAL SETUP, TRAINING AND RESULTS

The safety of firefighters was a significant issue during the data extraction phase. Based on observations made from the initial fire training drills and due to the possibility of exposing firefighters to unnecessary and extreme risks, the datasets were extracted primarily from sensors fixed at variable heights on wheeled platforms. These platforms were pulled via harnesses especially in situations where the likelihood of device damage was high. Moreover, uncertainties in any sensor observations were addressed via redundant sensor setups where each sensor device was encased in a high-temperature-resistant enclosure with data stream compared against fixed thermocouples. The details of the model training and testing data extraction setup are given below:

1. **Data extraction setting:** 40-foot shipping container with wooden fuel stacked at the far end
2. **Sensor type:** Two K-type thermocouples mounted at 1.07m and 1.68m heights to emulate a firefighter’s waist and shoulder positions
3. **Fuel type/material:** Plywood
4. **Extraction mechanism:**
   - 60-value input/output sliding windows covering 30-second input/output data with readings taken at 2 hertz
   - 10-value input/output sliding windows covering 5-second input/output data with readings taken at 2 hertz
5. **Training datasets:**
   - Drill-1-1: Closed-container-pole-tests (CCP-TRN-1)(Fig. 5)
6. **Testing datasets:**
   - Drill-1-2: Closed-building-pole-tests (CBP-TST-1)
   - Drill-2-1: Closed-container-pole-test (CCP-TST-1)
occurred because of partial door openings. There were dual-unique STH patterns formed at stages where limited airflow

The extracted datasets showed distinct flashover profiles as

extracted was divided into 6 unique cycles that were used to

effect from the height of where the sensors were mounted.

be observed that ingress of air has a significant impact on

flashover initiation and the intensity of flashover also takes

actions undertaken by fire-fighters is shown in Fig. 7. It can

explained in the next section.

A detailed, stage-wise depiction of the impact of various

actions undertaken by fire-fighters is shown in Fig. 7. It can

be observed that ingress of air has a significant impact on

flashover initiation and the intensity of flashover also takes

effect from the height of where the sensors were mounted.

It was noted that sensors at lower height have a relatively

slow temperature rise and decrease behaviour. The data thus

extracted was divided into 6 unique cycles that were used to

train the underlying regression model.

PHASE 1 - INITIATION

At this stage, the fire was started and allowed to take hold at the far-end corner of the container (Fig. 6 (a)).

PHASE 2 - DEVELOPMENT

Phase 2 - Development: Once the flames were spread over the entire plywood surface, all openings to the container were closed to create an enclosed household compartment condition. The fire continued to burn with a restricted air supply like any other household fires (Fig. 6 (b)).

PHASE 3 - BACKDRAFT INDUCTION

Phase 3 - Backdraft induction: Conditions like a door or window opening/breaking were created where the top and bottom door sections were opened interchangeably (Fig. 6 (c – d)).

PHASE 4 - FLASHOVER OCCURRENCE

Phase 4 - Flashover occurrence: Phase 3 generated a backdraft condition as the fire was exposed to additional air leading to an increase in fire intensity and a gradual temperature increase eventually leading to a flashover (Fig. 6 (e-f)).

PHASE 5 - SUPPRESSION

Phase 5 - Suppression: The fire was suppressed via a standard gas cooling mechanism to a slow-burning stage.

A detailed, stage-wise depiction of the impact of various actions undertaken by fire-fighters is shown in Fig. 7. It can be observed that ingress of air has a significant impact on flashover initiation and the intensity of flashover also takes effect from the height of where the sensors were mounted. It was noted that sensors at lower height have a relatively slow temperature rise and decrease behaviour. The data thus extracted was divided into 6 unique cycles that were used to train the underlying regression model.

B. SYSTEM EVALUATION AND ANALYSIS

The extracted datasets showed distinct flashover profiles as unique STH patterns formed at stages where limited airflow occurred because of partial door openings. There were dual-unique STH cases as well where the two-part doors were opened separately as evident between 11:24:07 and 11:27:08 time range shown in Fig. 7. The model trained on these datasets was then used against dataset described earlier-on in this section covering several containers and building setups, mounted platforms (body, poles, fixed) and heights. Two unique testing categories were used to evaluate the effectiveness of the proposed model – short and medium duration. The short-duration category was used to assess the effectiveness of the system against temperature fluctuations occurring at very short intervals of less than 5 seconds. The concept behind short-duration modelling was based on an observation made in one of the tests where a firefighter was exposed to an accidental flashover as he entered the testing container resulting in exposing the fire to add air. In that case, the transition from pre-alarm to flashover was only 4 – 5 seconds. The medium-duration case was used to predict the STH patterns forming around a 30-second window to allow firefighters more time to vacate.

There were 5 datasets involved in total for system evaluation where the initial CBP-TST-1 recorded random fire incidents created in a building where various doors and windows were opened or closed at random and CBP-TST-2 showed dataset extracted from a firefighter’s body-mounted sensor (Fig. 8). Fire suppression was frequently done preceded by the closing of all vents to allow the fire to grow again. The thermocouples, in this case, were mounted on a fixed pole which was not withdrawn at all during the entirety of the test. This mode showed the highest level of temperature prediction accuracy at 90% for 30-second intervals. The short-duration tests, however, showed a comparatively lower prediction accuracy which can be attributed to a highly random pattern of repeated fire suppression and ignition that generally does not take place in real-world fire suppression cases.

C. EXPERIMENTAL OUTCOME AND RESULTS

The units were mounted at 0.8m on the fixed pole for pole-mounted tests with one of the instructors wearing a unit at shoulder height at a height lower than the regular pole height. The datasets were collected with four concurrently running sensors with two mounted on the pole and directly facing the fire and two mounted on a sidewall via thermocouples with the remaining recording equipment outside the burning compartment. This setup was developed to ensure that in the case of a total loss of a fire-facing unit including the onboard SD cards, the datasets from thermocouples were still recoverable. The peak temperatures seen by the units were approximately 600 °C whereas those from body-worn units recorded a maximum of 100 °C due to the fact the firefighters only got as close to the fire as was deemed necessary based on their operational duties. The data loggers at 0.8m and 1.42m that ran for the full duration of both the burns recorded temperatures of more than 1000 °C. All datasets successfully identified pre-alarm and full alarm conditions with the predicted temperatures ranging between 150 – 299 °C and 300+ °C respectively (TABLE 1.).
FIGURE 6. Live-fire burning exercise phases during the training data extraction drill (CCP-TRN-1) (a) Incipient, (b) Developing (oxygen restricted) (c) Backdraft (oxygen fuelled) (d–e) Flashover start.

FIGURE 7. Impact of various events on the temperature variation profile during the execution of Stage 1 to Stage 5 fire drills for training data extraction.

Fig. 8 shows the ANN predictive outcome mapping to the SOM categorical classifier based on the CCP-TRN-1 training model. The longest prediction time was found for CCP-TST-1 with a window of 68.5 seconds. The shortest prediction times were found with test cases OCSM-TST1, CCP-TST-2 and OCST-TST-2 with advanced warnings generated at 42, 42.5 and 49.5 seconds respectively before the actual flashover temperature occurrence of 300 °C. The pattern similarities
Figure 8. Figures illustrating TSH pattern prediction against Stage-1 ANN prediction outcome for datasets (a) CCP-TST-1, (b) CCP-TST-2, OP59: 59th Output (predicted) value from the Stage-1 ANN classifier.

Table 1. Prediction accuracy of the ANN classifier for 5 and 10-second prediction windows with seconds indicating the duration before the 300 °C threshold was reached.

|        | 30-seconds-ahead (60-values) | 5-seconds-ahead (10-values) | Full-Alarm (60-values) | Full-Alarm (10-values) |
|--------|-----------------------------|-----------------------------|------------------------|------------------------|
|        | Accuracy (%) | Accuracy (%) | Seconds | Seconds |
| CRP-TST-1 | 89.99            | 78.51            | Not reached | Not reached |
| CCP-TST-1 | 83.73            | 96.27            | 68.5        | 182        |
| CCP-TST-2 | 89.134          | 95.03            | 42.5        | N/A        |
| OCSM-TST-1 | 84.68          | 87.81            | 42          | N/A        |
| OCSM-TST-2 | 88.37          | 95.33            | 49.5        | N/A        |

Table 2. Pre-Alarm (PA) and Flashover (FO) prediction accuracies and time before the actual flashover temperatures were reached for various datasets.

|        | FO | PA | Heads (C) | Shldrs (C) | Acc | PA time | FO time |
|--------|----|----|------------|------------|-----|---------|---------|
| CCP-TST-1 | 1 | 1 | 1 | 1 | 100% | 72 | 58.5 |
| CCP-TST-2 | 2 | 2 | 2 | 2 | 100% | 328 | 21 |
| OCSM-TST-1 | 6 | 7 | 4 | 6 | 76.92% | 276.5 | 17 |
| OCSM-TST-2 | 4 | 5 | 4 | 5 | 100% | 38 | 19.5 |

can be attributed to the relatively repetitive nature of the three cases whereas (a) only had a single flashover cycle. Moreover, the cases (b), (c) and (d) also went through elevated, lower temperatures after every fire suppression cycle which lead to a quicker flashover occurrence the next time the burn cycle was repeated.

The CCP-TRN-1 model was initially trained against the NIST Living Room dataset where it showed an overall 9-second and 36-second Pre-Alarm triggering in advance for the two temperature spikes of 270 and 610 °C respectively (Fig. 2).

Table 2 shows the performance outcome of the SOM classifier as it identified STH patterns for the four dataset cases CCP-TST-1, CCP-TST-2, OCSM-TST-1 and OCSM-TST-2. The approach successfully managed to find Pre-Alarm and Flashover categories in most of the cases apart from the OCSM-TST-1 where it did not identify the first two lower thresholds between 300 and 350 °C. This dataset was recorded under conditions where the fire was not completely suppressed and was then allowed to grow again at higher rates of 150+ °C. The last two columns in Table 2. show the time taken after the prediction for the actual Pre-Alarm or Flashover temperatures to occur. OP59 represents the 59th value ahead of prediction. Hence, any values shown are already 30 seconds ahead when compared to the predicted STH class directly beneath it. Based on this, CCP-TST-1 showed the best prediction time of 58.5 seconds before the actual flashover occurred. The same dataset also predicted a shoulder pattern 72 seconds ahead of reaching a temperature of 300+ °C. The system took 19.5 seconds to predict flashover and 38 seconds to identify the Pre-Alarm case (OCSM-TST2) which represented a shoulder-mounted case. This differed significantly from the OCSM-TST-1 where the Pre-Alarm stage was very long whereas the Flashover stage was only identified 17 seconds before reaching temperatures exceeding 300 °C. This disparity can be attributed to several reasons. Firstly, flashover occurrences in OCSM-TST-1 were very close and the room was not allowed to properly cool down. Hence, the system continuously remained in a Pre-Alarm condition. Secondly, repetitive burn cycles do not represent real-world fires which only have one burn cycle in general. The outcomes verified the hypotheses at the beginning of this work as follows:

**Hyp₁**: The ANN algorithm successfully predicted the flashover temperatures at least 30 seconds ahead in time with an average accuracy of 87.18%

**Hyp₂**: The two rate of temperature change class patterns, Pre-Alarm and Alarm were successfully reached in 11 out of 13 cases with an accuracy of 84.61% whereas the shoulder patterns were predicted correctly in 14 of 15 cases with an accuracy of 93.33%. On average, the Alarm stage was predicted 29 seconds ahead of the actual occurrence.
Hyp$_3$ : The ROT increase pattern followed a STH pattern in all the cases individually observed with the neutral plane lowering during all the burning cycles before reaching the flashover stage.

In addition to the abovementioned hypotheses confirmation, the following observations were made:

- Body-mounted sensors demonstrated a limited temperature range based on firefighters natural operating behaviour. Hence, in several cases, the prediction outcome was limited to Pre-Alarm classification only.
- Pole-mounted tests showed a more realistic model behaviour, especially the sensors at lower (1.07m) heights. This was since most firefighters remain in crouching positions during fire-suppressing events.
- Along with the validation of Hyp$_3$, distinct flame sparks were noticed on ceilings moving away from the burning section as visual indicators a few seconds before the actual flashover occurrence.
- It was also noted that despite the flashover initiating, there was still a small, few second windows where the neural plane stayed 1.5 – 2 feet above the ground and hence allowed further time for individuals to crawl out of the area.

In the proposed methodology, the most critical outcome was obtained via a ANN regression-based outcome. The proposed SOM technique itself is used here to eliminate false positives resulting from random input temperature peaks. Any false output peaks in regression are hence eliminated due to the distance from any of the sliding-window class clusters i.e. Normal, Pre-Alarm or Flashover. In addition to the SOM-based outlier elimination mechanism, a boundary-detection or threshold-checking mechanism was introduced which continuously evaluated the regression model output for unexpected outliers. For instance, any continuously low regression outcome predicted by the algorithm when the raw exogenous temperature feedback directly from the sensor was very high was flagged and ignored by the regression model and not fed into the SOM classifier.

V. CONCLUSION AND FUTURE WORK

The work addressed two significant areas of interest in the nonlinear fire behaviour prediction domain with core
applications in industrial and fire & rescue temperature prediction and warning. The work applied a sliding-window, external variable-driven approach to predict future temperature ranges in burning buildings. The second stage focussed on the elimination of false positives due to random exposure of temperature sensors to short-term, high-temperature spikes in burning buildings. Several tests were performed to ensure the viability of these results including remotely handled platforms/mannequins, human-body mounted thermocouples, prototypes encased in heat-resistant casings and completely closed full-burn cycles recorded by wall-mounted thermocouples.

The ANN classifier was evaluated in a prototype embedded device designed as a practical, firefighter-worn unit, which is described in more detail by Yusuf and Garrity [30], [31]. The first set of results were primarily meant to evaluate an ANN model trained on NIST fire data to evaluate its sensitivity in live-fire environments. The model did show its resilience against noisy datasets, particularly in cases where full burn cycles from the development to cooling phase were performed.

As this is an ongoing work, it does aim to extend to several cases that have not been tested so far. The time-series data obtained largely has been limited to shorter-length windows of less than a minute. Using memory-based systems such as long short-term memory (LSTM) and gated recurrent units (GRUs) are likely to improve the accuracy of the overall system by retaining previous/intermediate, partial
fire suppressions. Moreover, the system does not take other factors into account such as gas levels composition and heat flux into account which may substantially affect the accuracy of prediction of this algorithm.

**APPENDIX**

**HYPERPARAMETER TUNING OF SOM**

A SOM comprising of a single layer 2D grid of neurons was used instead of a series of layers. The nodes on this 2D grid were connected directly to the input vector. Hence, each node was not aware of its neighbouring values whereas the weights were only updated as a function of their given inputs. The grid, in this case, forms a map that organises itself as a function of the input data. Hence, after clustering, each node on the grid is represented as two coordinates \((i, j)\). This enables the calculation of the Euclidean distance between any two nodes which facilitates the so-called self-organising, unsupervised clustering and hence categorisation of the data model.

The variables, instead of ANN parameters, that define a SOM are given below:

- \(t\) : the current iteration in the SOM modelling process
- \(n\) : the total iterations a network can perform
- \(\lambda\) : the time constant variable used to decay the learning process and radius
- \(j\) : the column coordinate of the representative grid
- \(d\) : the Euclidean distance between the node and the best matching unit
- \(w\) : the weight vectors
- \(w_{ij}(t)\) : the connection weight between the nodes \((i, j)\) in the grid and the \(t^{th}\) input vector’s instance
- \(x\) : input dataset vector
- \(x(t)\) : input dataset vector at iteration \(t\)
- \(\alpha(t)\) : the learning rate that decreases with time
- \(\beta(t)\) : the neighbourhood function that decreases monotonically and represents the Euclidean distance of a node \((i, j)\) from its best matching unit as well as the influence it has on the learning at the iteration \(t\)
- \(\sigma(t)\) : the radius of the neighbourhood function that describes the distance measure of the circle of neighbouring nodes on the 2D grid during vector updates. The radius gradually reduces with time.

**A. SOM ALGORITHM**

1) **Initialisation:** Initiate each node \(n_{ij}\) weight \(w_{ij}\) to a random value

2) **Training:**
   a) Select an input vector \(v(t)\) randomly
   b) For ALL nodes, repeat steps (i) and (ii)
      i) Compute Euclidean distance \(ED_t\) between input vector \(v(t)\) and the weight vector \(w_{ij}(t)\) associated with the first nodes where \(t = i = j = 0\)
      ii) Track the node with the smallest \(ED_t\)
   c) Find the overall best matching unit \(N^t\) which is the node with the smallest distance from all calculated distances
   d) For each \(\beta(t)\), determine its radius \(\sigma(t)\) of the best matching \(N^t\)
   e) Repeat for all nodes in the \(N^t\) neighbourhood
      i) Update the weight vector \(w\) of the first node in the neighbourhood
      ii) Add a fraction of difference between the input vector \(x(t)\) and weight vector \(w(t)\) of the neuron
   f) Repeat the entire iteration until the iteration limit \(t = n\) is reached

**ACKNOWLEDGMENT**

This work was supported by the Deanship of Scientific Research (DSR), King Abdulaziz University, Jeddah, under grant No. (DF-137-611-1441). The authors, therefore, gratefully acknowledge DSR technical and financial support.

**REFERENCES**

[1] J. A. D. Puortori and J. McElroy, “interFIRE, A site dedicated to improving fire investigation worldwide,” Nat. Inst. Standards Technol., Gaithersburg, MD, USA, Tech. Rep. FR 4009, 1998.
[2] V. Babrauskas, “Estimating room flashover potential,” Fire Technol., vol. 16, no. 2, pp. 94–103, May 1980.
[3] D. Madrzykowski, Fatal Training Fires: Fire Analysis for the Fire Service. Gaithersburg, MD, USA: National Institute of Standards and Technology, Building and Fire Research, 2007.
[4] J. R. Lawson, “Fire fighters’ protective clothing and thermal environments of structural fire fighting,” in Proc. 6th Perform. Protective Clothing. West Conshohocken, PA, USA: ASTM International, 1997, pp. 334-1–334-19, doi: 10.1520/STP19915S.
[5] V. Babrauskas, “Combustion of mattresses exposed to flaming ignition sources. Part 2. Bench-scale tests and recommended standard test,” NIST, Gaithersburg, MD, USA, NIST Interagency/Internal Rep. NBSIR 80-216, 1981, doi: 106997.
[6] J. B. Fang, “Fire endurance test of selected residential floor constructions,” NIST, Gaithersburg, MD, USA, NIST Interagency/Internal Rep. NBSIR 80-2120, 1982, doi: 106930.
[7] E. K. Budnick and D. P. Klein, “Mobile home fire studies: Summary and recommendations,” Gaithersburg, MD, USA, NIST Interagency/Internal Rep., 1979, doi: 107011.
[8] J. B. Fang and J. N. Breese, “Fire development in residential basement rooms,” Nat. Bureau Standards, Gaithersburg, MD, USA, Tech. Rep. NBSIR 80-2120, 1980, doi: 10.6028/826 NBS.IR.80-2120.
[9] A. N. Beard, “Dependence of flashover on assumed value of the discharge coefficient,” Fire Saf. J., vol. 36, no. 1, pp. 25–36, 2001, doi:10.1016/S0379-7112(00)00048-5.
[10] V. Novozhilov, “Flashover control under fire suppression conditions,” Fire Saf. J., vol. 36, no. 7, pp. 641–660, 2001, doi:10.1016/S0379-7112(01)00019-4.
[11] U. Wickström, Temperature Calculation in Fire Safety Engineering, vol. 58. Cham, Switzerland: Springer, 2016, doi: 10.1007/978-3-319-30172-3.
[12] Y.-Y. Zhang, X.-Z. Li, and Y. Liu, “The detection and defence of DoS attack for wireless sensor network,” J. China Univ. Posts Telecommun., vol. 19, pp. 52–56, Oct. 2012, doi:10.1016/S1005-8855(11)60444-5.
[13] H. Gellersen, P. Lukowicz, M. Beigl, and T. Riedel, “Cooperative relative positioning,” IEEE Pervas. Comput., vol. 9, no. 4, pp. 78–89, 2010, doi: 10.1109/MPRV.2010.19.
[14] N. Simon, J. Bordoy, F. Hoflinger, J. Wendeberg, M. Schink, R. Tannhauser, L. Reindl, and C. Schindelhauer, “Indoor localization system for emergency responders with ultra low-power radio landmarks,” in Proc. IEEE Int. Instrum. Meas. Technol. Conf. (I2MTC), May 2015, pp. 309–314, doi: 10.1109/I2MTC.2015.7151285.
[15] C. Zhong, J. Eliasson, H. Makatiavola, and F. Zhang, “A cluster-based localization method using RSSI for heterogeneous wireless sensor networks,” in Proc. Int. Conf. Comput. Intell. Softw. Eng., Sep. 2010, pp. 1–6, doi: 10.1109/ICCIW.2010.5601356.
[16] A. Das, P. Beatty, and R. Dutta, “Estimation of physiological body parameters from smart garment data,” in Proc. IEEE Int. Instrum. Meas. Technol. Conf. (I2MTC), May 2014, pp. 86–90, doi: 10.1109/I2MTC.2014.6860706.
SYED ADNAN YUSUF is currently with the Senior Data Scientist at Elm, Riyadh, Saudi Arabia, where he is leading various teams working in the domains of document verification, facial identity analysis and traffic violation. In his previous role with Hitachi Europe he led a team of scientists and engineers developing autonomous perception and motion planning systems for the Nissan Leaf Electric. The work led to a fully autonomous 200+ mile journey on a variety of U.K., roads as part of the Human Drive project. In the research domain, his focus is on CNN/RNN algorithms with a focus on driverless autonomous control and video analytics systems and deep residual networks for the face recognition domain.

RAYED ALGHAMDI received the B.S. degree in computer science from Jadiah Teachers’ College, Saudi Arabia, in 2003, and the M.S. and Ph.D. degrees in information and communication technology from the School of Information and Communication Technology, Griffith University, Brisbane, Australia, in 2008 and 2014, respectively. He is currently an Assistant Professor with the Faculty of Computing and Information Technology, King Abdulaziz University (KAU). He serves as a Consultant for Teaching and Learning Development, KAU. His research interests include diffusion and technology adoption and information technology education.

MADINI O. ALASSAFI received the B.S. degree in computer science from King Abdulaziz University, Saudi Arabia, in 2006, the M.S. degree in computer science from California Lutheran University, USA, in 2013, and the Ph.D. degree in security cloud computing from the University of Southampton, Southampton, U.K., in April 2018. He is currently working as an Assistant Professor with the Information Technology Department, Faculty of Computing and Information Technology, King Abdulaziz University. His research interests include cloud computing and security, the Internet of Things (IoT) security issues, and data science for deep learning topics.

ABDURALHMAN A. ALSHDADI received the B.S. degree in computer science from Taif University, Saudi Arabia, in 2008, the M.S. degree in information technology from the School of Computer Science, Nottingham University, U.K., in 2010, and the Ph.D. degree in cloud computing from the University of Southampton, Southampton, U.K., in February 2018. He is currently working as an Assistant Professor with the Information Technology Department, Faculty of Computing and Information Technology, University of Jeddah. He has published numerous conference papers, journal articles, and one book chapter. His research interests include cloud computing migration projects and security, the Internet of Things (IoT) security issues, and data science for deep learning topics.