

Advanced Computing and Sensing to Improve Mine Fire Characterization and Response

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(ABSTRACT)

After fire is discovered in an underground coal mine, a decision must be made to mitigate fire consequences. The decision should be made based on existing conditions, with the goal of increasing the probability of fire extinguishing without compromising the health and safety of the firefighting personnel. However, the determination of fire conditions can be difficult due to coarse in-situ measurements, fire hazards, and the large domains of interest. Additionally, CFD and network models used for predicting fire conditions are computationally expensive with long simulation processing times for informing real-time decision making. A new generalized procedure to design artificial neural networks (ANNs) capable of making predictions of fire conditions, performing hazard/risk assessment, and providing useful information to the firefighters is presented and applied to different underground coal mine fire scenarios. The feed-forward ANNs were developed to classify fires so as to provide the best firefighting decision and determine useful information in real time, such as response time and fire size. The networks were trained to make predictions on different mine locations and to use only available and measurable information in underground coal mines as inputs. The data used for training and testing the networks was generated using high-fidelity CFD and network fire simulations. Additionally, this research presents the applicability of optical fiber sensing technology for continuous, distributed, and real-time sensing. This new technology could be used for collection of input parameters during ongoing fires, leading to improvement of the prediction performance of the ANNs developed. Finally, a new approach to simulate firefighting foam flow through gob areas is proposed and tested using experimental results obtained from a scaled down experimental setup.

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(GENERAL AUDIENCE ABSTRACT)

Mine fires still represent a serious hazard in underground coal mines. The MSHA incident database shows that around 600 mine fire incidents and 33 fatalities were reported in the U.S. during the last two decades. Most fatalities and injuries that occurred in the aforementioned incidents can be attributed to lack of knowledge on existing fire conditions, leading to poor subjective decisions during fire response. Unfortunately, the in-situ determination or prediction of fire conditions are not easy tasks due to fire hazards, mine entries extensions, and simulation processing times. For this reason, this work presents new data-driven models capable of predicting and evaluating fire conditions. Its goal is to recommend the most suitable firefighting decision, as well as determine fire characteristics and response time to increase the probability of fire extinguishing without compromising mine personnel health and safety. These data-driven models are composed of artificial neural networks (ANNs), allowing for performing predictions in real time and using only available information in underground coal mines. The data used for training and testing these ANNs was generated from fire simulations. Additionally, this research proposes a new technology, such as optical fiber sensing for continuous, distributed, and real time sensing. Optical fiber sensing could contribute with more precise ANNs inputs collection, leading to a better performance prediction. Finally, an alternative way to simulate firefighting foam through gob areas for fire mitigation was proposed and tested using results obtained from experiments. This work represents a significant advancement in underground coal mine fire characterization and response.

Dedication

Dedicated to:

My Wife

My Mother

My sister

My Grandparents: Manuel and Paulina

Thanks for your love and support

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Chapter 1

Introduction

1.1 Motivation

Although great advances regarding the understanding of mine fires have been achieved, they still represent a serious hazard and are omnipresent in underground coal mines [18]. Around 600 mine fire incidents were reported in the last two decades in the U.S, of which three were classified as fatal incidents according to the MSHA incident database. The three fatal events were the Upper Big Branch explosion in 2010 (29 fatalities), Alma Mine Fire in 2006 (2 fatalities), and the Willow Creek Mine explosion in 2000 (2 fatalities) [20]. It is important to mention that although in two of these three fatal incidents fatalities were produced by explosions, a fire was the fundamental cause. Based on the reported fire events, it can be evidenced that small fires can occur in any underground mine location and extent quickly if they are not controlled, producing larger and more serious consequences [17, 18]. If a mine fire cannot be put out within a short time after discovery, the chance of getting the mine back in balance and the success of safely extinguishing the fire are greatly reduced [8, 17, 18, 100]. However, direct extinguishment must be carried out without compromising the health and safety of the firefighting personnel. Thus, “a good emergency response can mean the difference between a minor incident and disaster” (Conti) [17].

When a fire is detected in an underground coal mine, three main possibilities for firefighters are available: remaining in the mine to carry out direct attack, remote attack from adjacent

fire locations, or mine evacuation for remote attack from the surface. It is noteworthy that the selection of the decision depends mainly on the mine fire conditions. Thus, the likelihood of making the most suitable decision relies on the knowledge of existing mine atmospheric conditions. However, there is no evidence of tools that can determine the existing conditions and predict the potential evolution of these conditions in real-time during ongoing mine fire scenarios. In addition, it is currently observed that decisions made by mine firefighters are mainly subjective based on personnel experience, which can lead to mistakes. Thus, tools that can predict fire conditions in real time could allow for more information in the decision-making process. Real time predictions refers to the fact of the tools of predicting outcomes instantaneously after parameters are input in the trained models.

Computational fluid dynamics (CFD) and zone fire models have been used to predict mine fire conditions. CFD models solve the conservation equation of mass, momentum, and energy for each grid cell in a discretized domain [69, 71]. CFD models allow for predicting high spatial-temporal resolution of parameters with direct influence on the mine fire conditions. However, the computational cost and simulation times make CFD models unfeasible on the determination of the mine fire conditions in real-time during ongoing fire scenarios. On the other hand, in zone fire models the domain is divided into compartments with a significant volume, allowing for the reduction of the computational cost and faster predictions [28]. However, though faster predictions can be achieved by zone fire models, using these models is still unfeasible for rapid determination of the best decision during active fires, since predictions need to be analyzed and their resolution is low for hazard and risk analysis.

A method that can be implemented to make instantaneous predictions of the mine fire conditions, and at the same time analyze them to provide useful information for the decision-making process, is the use of artificial neural networks (ANNs). ANNs can learn complex dependencies between variables which makes them an attractive technique to develop ap-

proaches based on numerical results. Many studies have reported the successful use of ANNs to generate data-driven approaches to predict parameters in various fields such as remote sensing [7, 51], climate modeling [26, 56, 90], and wildland fire spread [12, 42]. In addition, in the fire protection engineering field some data-driven approaches have been focusing on predicting the parameters that directly affect the fire conditions in enclosed spaces [42]. However, the research presented in this document involves the mine fire characterization and risk analysis in real time, using only information available in underground coal mines, thus allowing for less subjective emergency response decisions.

1.2 Research Overview and Contributions

This research represents a significant advancement in the field of fire risk and hazard analysis in underground coal mines. Prior to the present study, decisions carried out during mine fire scenarios were made merely based on the experience of the firefighting personnel and previous training. Using the tools proposed in this study, it is possible to make predictions of conditions to classify fires or determine response times in real-time, allowing for less subjective decisions. This fact increases the probability to put fires out without compromising the health and safety of firefighting personnel. Furthermore, using the tools presented in this research it is possible to perform fire risk and hazard analysis in large domains such as, underground mine locations.

This research also signifies progress in data-driven approaches for fire conditions predictions in enclosed spaces. Before this research, data-driven approaches were focused on predicting parameters in individual points or spatially resolved grids that have direct influence on the fire conditions. Such predictions were processed and analyzed later for fire safety design and risk analysis. However, the data-driven approaches presented in this research can predict

and analyze those parameters in real-time during mine fires.

Moreover, this research represents a considerable advancement in the field of coal mine fire sensing and determination of the status of the mine atmosphere during existing fires. Prior to the tools presented here, there is no evidence of an approach or methodology that can predict fire characteristics and the conditions at the proximity of the fire based on online real time measurements by permissible sensors in underground coal mines. Although the information obtained during underground coal mine fires is limited due to permissibility issues, the tools of this study can perform precise predictions of mine fire conditions. In addition to this, a new technology of gas sensing in underground coal mines is presented that can contribute to information collection during mine fire events, allowing for more precise predictions by the developed data-driven approaches.

The data-driven approaches elaborated during this research also contribute to the compliance of the mining regulation. Specifically, Title 30 CFR § 75.1502b regulation which requires that each operator of an underground coal mine has an emergency and firefighting program that instructs all miners in the procedure that they must follow if a fire occurs. The models proposed have the capability of providing useful information and recommend the best plan of action for each specific fire emergency. Additionally, these models can be used for training and preparing the firefighting personnel prior to fire occurrence. They can be used to simulate multiple fire scenarios building confidence and skills levels on firefighters, as well as train them on what to expect in the event of a fire regarding the relationship between fire conditions evolution, deployment time, and firefighting decision.

The last part of this research can be seen as an advancement in mine remote firefighting and foam modeling. A simpler approach to simulate firefighting foam as a non-Newtonian fluid through mine gob areas was tested, using experimental data collected from a scaled down experimental setup. Predictions of foam flow in these areas allow for determining optimal

operational parameters during foam injection, and consequently improving the efficiency of this technique. Although further experimental studies are required, this is a first contribution to reduce the complexity of foam modeling through porous media.

The contributions of this research can be summarized as follows:

ANN for classifying fires based on the most suitable decision using available parameters during ongoing mine fire scenarios.

A data-driven approach that can provide the most suitable decision to the mine firefighting personnel in real time during underground coal mine fires using a feed-forward ANN was developed. The methodology along with the concepts that should be considered to elaborate a data-driven approach of this type were detailed. The data-driven approach was used to classify fires in a flat and straight mine entry, based on readings by permissible sensors in underground coal mines. Scenarios with different fire size, air velocity, fire growth rate, and mine entry dimensions were simulated in FDS and FSSIM for data generation to train and test the model. It is noteworthy that the the data-driven approach elaborated in this study is site-specific, which means that it can be used only in similar geometries of fire scenarios utilized for training.

ANN for determination of response time and fire size using parameters available and measurable in underground coal mines during ongoing fires.

Two interconnected ANNs were trained and tested to predict response times and fire sizes based on online real-time CO concentration readings downwind from the fire. Fire scenarios at a straight and flat mine entry with different fire sizes, ventilation configurations, and dimensions were simulated using FDS and FSSIM. Simulation results were used for training and testing the ANN models.

ANNs for classifying conveyor belt fires and analyzing the effects of design pa-

rameters and air velocity on fire class.

An ANN was created to classify conveyor belt fires based on the most convenient decision that must be made by firefighting personnel. Furthermore, some simple ANNs were created to study the influence of air velocity and design parameters such as belt position, tunnel height, and width on fire class. With the objective of getting realistic results, CFD model validation was carried out using experimental test results available in the existing literature.

Numerical model validation and modeling of foam solution through porous media.

A simpler approach to simulate foam as a non-Newtonian fluid through gob areas was tested using experimental data obtained from a scaled down experimental setup. Results show the capability of this approach to replicate experimental results, which would allow for reducing the complexity of modeling foam as a multiphase flow in porous media.

Proposal of a new technology of gas sensing in underground coal mines, and its applicability in longwall mining.

Details of the current state-of-the-art in gas sensing in underground coal mines and optical fiber sensing were introduced. Additionally, the applicability of optical fiber sensing technology for continuous and distributed sensing of gases at the longwall face is presented, along with preliminary design for a full-face sensor.

1.3 Outline

This manuscript is organized in chapters where each one is a paper associated with the contributions mentioned previously. In Chapter 2, the methodology and concepts to develop a mine fire classification using an ANN are presented. Chapter 3 presents the use of two inter-

connected neural networks for prediction of response time and fire size during ongoing mine fires. Chapter 4 shows an ANN developed to classify belt fires based on design parameters and ventilation conditions. Furthermore, simple ANNs were used to study the influence of design parameters and air velocity on fire classification. Chapter 5 shows the evaluation of a new approach to simulate firefighting foam through gob areas using data collected from an experimental setup. Chapter 6 presents the conclusions of this research and possible future work. Appendix A presents the limitations of current mine sensing and the applicability of optical fiber sensing technology for continuous and distributed sensing of gases at the longwall face.

1.3.1 Previously published work statement

This dissertation is based in part on the previously published or under review articles listed below. I have permission from my co-authors/publishers to use the works listed below in my dissertation.

- Barros-Daza, M., Luxbacher, K. D., Lattimer, B. Y., & Hodges, J. L. (2021). Mine conveyor belt fire classification. *Journal of Fire Sciences*, 073490412110563. <https://doi.org/10.1177/07349041211056343>
- Barros-Daza, M., Ripepi, N., Zhu, Y., Pickrell, G., Luxbacher, K. D., Shi, G., Homa, D., & Su, X. (2019). Applicability of distributed optical fiber sensing for a longwall face. *SME Annual Conference & Expo*.
- Barros-Daza, M., Luxbacher, K. D., Lattimer, B. Y., & Hodges, J. L. Fire size and response time predictions in underground coal mines using neural networks. Under review in *Mining, Metallurgy & Exploration*.

- Barros-Daza, M., Luxbacher, K. D., Lattimer, B. Y., & Hodges, J. L. Real time mine fire classification to support firefighter decision making. Under review in Fire Technology.

Chapter 2

Real time mine fire classification to support firefighter decision making

2.1 Abstract

This paper presents a data-driven approach that can provide the most suitable decision to the mine firefighting personnel in real time during ongoing underground coal mine fires. The approach uses a feed-forward artificial neural network (ANN) to classify fires to provide the best decision considering only parameters measurable in underground coal mines. Additionally, the methodology along with the concepts that should be considered to elaborate a data-driven approach of this type are detailed. A total of 500 fire scenarios with different fire size, air velocity, fire growth rate, and entry dimensions were simulated in Fire Dynamics Simulator (FDS) and Fire and Smoke Simulator (FSSIM) for data generation to train and test the model. Results show that the ANN predicted fire classes with an accuracy and weighted-average F1-score equals to 97% and 96.7% for training and testing dataset, respectively. Results also show that 95% of ANN predictions of fire class change should not have a time gap greater than 18 s of the true fire class change for any fire position in the tunnel. Furthermore, the impact of fuel uncertainty during mine fires and how to address it is discussed in this paper. While the model presented in this work was designed to classify fires in a regular elongated coal mine entry, the same methodology could be applied to

classify fires in other scenarios with similar geometry, such as road tunnels.

2.2 Introduction

Although there have been great advances regarding the understanding of the causes of fires in underground mines, small fires continue to occur and are difficult to eliminate entirely. Mine fires can grow and develop rapidly and are considered high risk events due to risks of explosion and logistics of personnel evacuation. Thus, the time elapsed during the detection and response is a critical element. If a mine fire cannot be put out within a short time after discovery using direct fire-fighting techniques, the chance of extinguishing the fire without sealing the mine or a portion of the mine is significantly reduced [18]. Direct fire extinguishing is preferred since it is possible to mitigate the hazard before it grows significantly; however, direct attack can compromise the health and safety of firefighting personnel if conditions grow untenable. Unfortunately, most decisions made by mine firefighters are based on a subjective interpretation of available data, which can lead to dangerous mistakes. There is a need for a new approach which is able to objectively analyze all available data and help firefighters identify the most suitable decision based on existing conditions of the fire scenario.

The determination of conditions in a mine during ongoing fires can be difficult due to coarse in-situ measurements and the large domains of interest. Researchers have successfully used tools such as computational fluid dynamics (CFD) to determine the conditions close to the fire [38, 47, 91, 109]. However, the high computational cost and processing time of these models makes it impractical to use in informing real-time decision making. An alternative approach which has the potential to overcome these limitations is to develop a deep learning-based surrogate model. The use of a data-driven approach that can classify fires based on

the most adequate decision determined by the mine atmosphere conditions is particularly promising for enhancing the safety of firefighters as well as increasing the probability of extinguishing a fire.

Advancements in machine learning techniques and computing power have contributed to an increase in the usage of artificial neural networks (ANNs) for this kind of application. ANNs can learn complex dependencies between variables making them an attractive technology to elaborate data-driven approaches based on CFD results or experimental data. Researchers have recently applied deep learning to the complex task of numerical simulations such as in the wake flow dynamics [55, 75, 83], turbulence modeling [54, 68] and multi-physics fire behavior modeling [11, 41, 42]. Each of these studies have shown the capability of ANNs to model complex behavior. With the objective of reducing computational time and cost associated to CFD fire model predictions in order to: to support hazard/risk assessments, use dispersed data to understand conditions, and develop mitigation strategies in large built structures [52], data-driven approaches based on CFD fire models have been presented during the last years. Hodges et al.[42] presented a data-driven generative model to predict spatially resolved temperatures and velocities within compartments. Hodges used a transpose convolutional neural network (TCNN) that was fed with zero-dimensional model results, geometry, and flow conditions parameters. Similarly, Buffington and Cabrera[11] presented a deep learning methodology for predicting temperatures within compartments using an array of artificial neural networks (ANNs). Nevertheless, it is worth mentioning that in Buffington's model, predictions were transient temperatures rather than spatial, as performed in Hodges' work. In addition, zero-dimensional model results were used for transfer learning rather than as input to the deep learning model.

The present work is similar to the studies mentioned because fire conditions are predicted using deep neural networks, but there are several key differences. First, the data-driven

model presented in this study predicts fire conditions and simultaneously analyses such conditions to classify the fire scenario and provide the most suitable decision. Second, the model inputs are parameters directly measured or available during the fire scenario, rather than calculated in reduced-orders models. Another key difference is the low number of inputs used. It is important to highlight that the information available during coal mine fires is very limited to point type parameter sensors due to the exclusive use of permissible electric equipment (Title 30 CFR 75.500) [101]. It is worth mentioning that there is no evidence of a similar approach to the one proposed in this study that can classify fires performing hazard/risk assessments and proposed mitigation strategies in real time.

The objective of this study was to develop a data-driven approach to classify fires in real-time based on on-site sensor readings and other available parameters during ongoing underground coal mine fires to recommend the most suitable decision to firefighters. The model was designed to classify fires in an elongated and flat mine entry, which is a common geometry in underground coal mines. Methodology and concepts considered for the model elaboration are detailed in this paper. The data-driven model consisted of a feed-forward ANN that was trained and tested using data generated from FDS and FSSIM simulations to classify fires in a belt entry. 500 fire scenarios with different fire size, air velocity, fire growth rate, and mine entry dimensions from FDS and FSSIM were linked and processed to be used as inputs and outputs in the ANN. Additionally, the data-driven model was tested for different fire locations and fuels to determine the impact of these two parameters on the model accuracy and provide recommendations. The following sections describe the methodology and concepts used during this study as well as the results and discussion of the implementation of the data-driven approach.

2.3 Methodology

The methodology for the data-driven approach to classify fires to provide the best information for decision making in real time during ongoing fires is based on the work of Hodges et al. [41] and Lattimer et al. [52] in which the authors defined the steps for the elaboration of data models in new physical applications. The methodology used in this study includes a literature review about the state of art of mine fire emergency response procedures, information available and measurable during underground coal mines to feed the approach, previous studies performed to evaluate the tenability in fire tunnels, and identification of parameters that affect fire conditions. In addition, the most important concepts accounted for the proposed mine fire classification as well as the procedure for the elaboration of the predictive model are included in this section. The methodology used in the study presented herein can be summarized in the following steps:

- Identification of firefighters' decisions during mine fires.
- Tenability analysis.
- Identification of parameters with influence on firefighting decision.
- Identification of parameters available during underground coal mine fires.
- Definition of the scope of the fire classification.
- Data generation.
- Data preparation.
- Elaboration of the ANN.

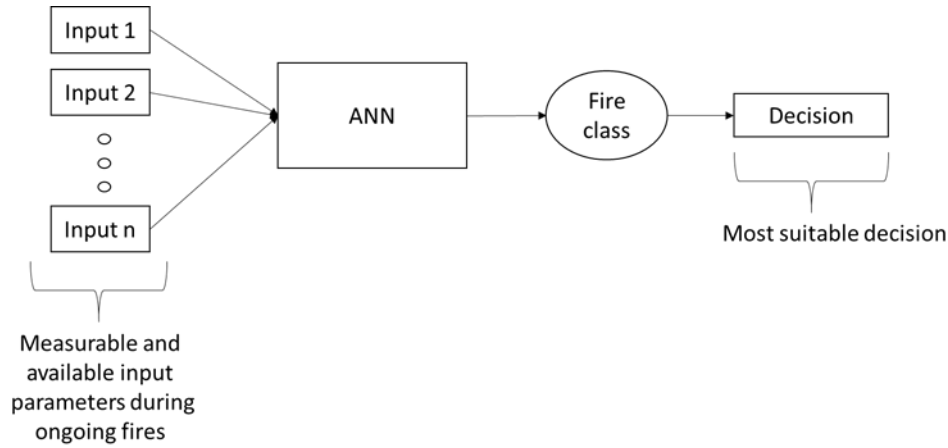


Figure 2.1: High-level view of the data-driven approach.

Each step of the methodology is detailed in the following subsections. This methodology was structured in this way in order to show the concepts and procedures considered to develop the data-driven approach. As mentioned previously, the objective of the data-driven approach is to classify fires using measurable input parameters during ongoing fires in which each fire Class is associated with recommended decisions and a description given to the firefighting personnel as shown in Figure 2.1. Figure 2.1 shows the high-level view of the data-driven approach proposed in this study.

2.3.1 Identification of firefighters' decisions during mine fires.

During fire scenarios, many crucial decisions and actions can be made that greatly influence the final consequences. From the moment that a fire has been discovered or fire alarm is activated, the first responder group (FRG) has to decide between three choices as shown in Figure 2.2. The first choice is to do nothing in case of a false alarm. The second one is to evacuate the fire area because of poor atmospheric conditions and the third choice is to approach or investigate the fire. Fire investigation can result in direct attack or section evacuation according to the conditions at the proximity of the fire. In the case that evacua-

tion has been determined to be the best course of action, the communication with a second responder group (SRG) must be performed in which information about the conditions is conveyed. This will help the SRG decide between performing a direct or remote attack. Additionally, two more choices for the FRG are available after section evacuation. The FRG can decide to go to a refugee chamber because conditions prevent mine evacuation. In this scenario, first responders can go to refugee chambers and wait safely until the fire is extinguished by the SRG or they are rescued by the mine rescue team [8]. Alternatively, the FRG can evacuate the mine through escapeways if it is possible [18].

As discussed above many decisions are involved during a mine fire scenario each of which has a direct influence on the final outcome. Therefore, it is necessary to have a technology that can help firefighters to make decisions based on the existing and potential conditions generated by the fire. In past mine fire incidents it has been shown that decisions were made without knowledge of actual conditions close to the fire, but rather with the intuition and experience of the firefighting personnel [18].

2.3.2 Tenability analysis

This analysis was carried out to determine the parameters and limits that should be considered for evaluating the mine atmospheric conditions to determine the best decision. The tenability analysis presented in this study is based on previous analyses performed in mine and road tunnels. A tenable environment is defined as an environment where human life can be supported [66].

US mining regulation requires that each operator of an underground coal mine has an emergency and firefighting program that instructs all miners in the procedure that they must follow if a fire occurs (Title 30 CFR § 75.1502b). The regulation specifies that during a

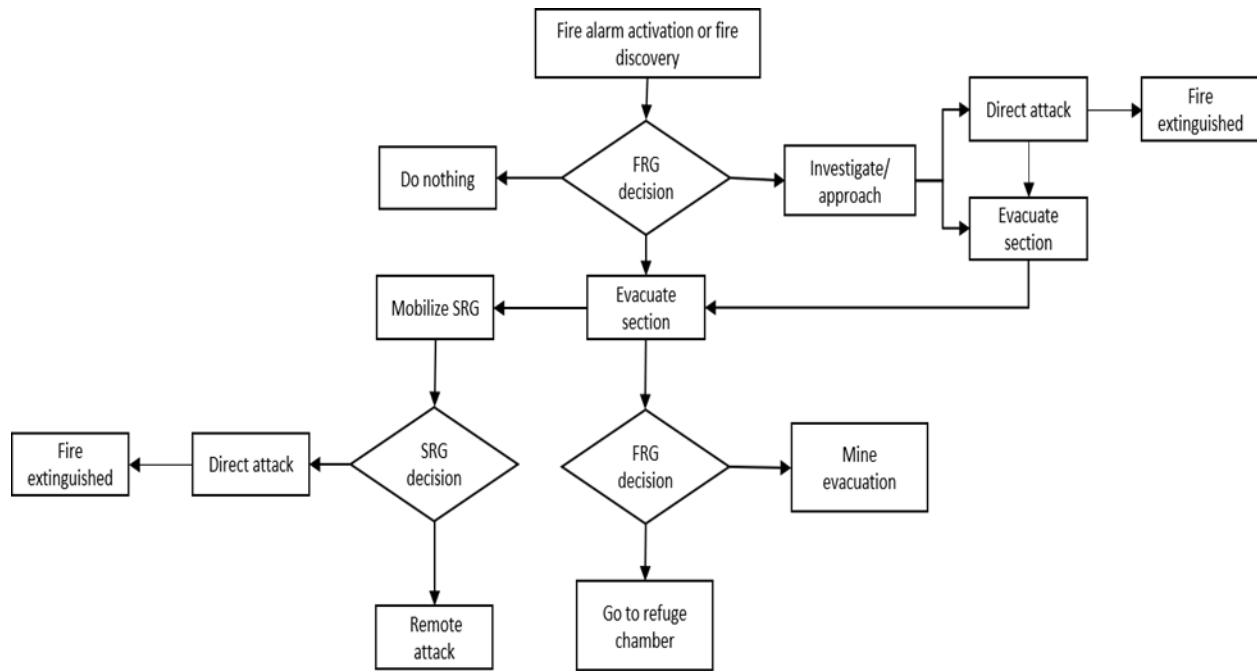


Figure 2.2: Possible decisions by firefighting personnel after fire alarm activation or fire discovery.

mine fire some miners are assigned to respond to the mine fire emergency while miners not required for the response must evacuate the mine. Mining regulation stipulates that at least two miners in each working section and one miner for every four miners on a maintenance shift should be proficient in the use of fire suppression equipment available in the mine (Title 30 CFR § 75.1503a, b, c). This barefaced personnel firstly in charge of dealing with the fire composes the FRG [18]. In case of backup it is required that the SRG is available to perform firefighting activities in more extreme conditions. Thus, it can be stated that the SRG has more specialized personal protective equipment, like turnout gear and self-contained breathing apparatus (SCBA). Additionally, the firefighting equipment of this group normally includes efficient water hose nozzles with pistol grips allowing the members of this group to fight fires for longer time comfortably and with more control of water patterns and flows [18]. In underground mining, the SRG groups are usually specially trained mine rescue or fire brigade teams.

Based on previous studies related to tenability analysis performed in tunnels [33, 39, 45, 78], four main parameters should be considered to determine if the firefighters' live can be sustained. Among these parameters are toxicity, temperature, visibility, and radiation. For toxicity, the most produced and harmful combustion gases such as carbon monoxide CO and carbon dioxide CO₂ are considered. It is noteworthy that for the SRG the toxicity is not accounted since this group normally carry SCBA designated to provide oxygen for at least 4 hours. Regarding temperature and radiation it is also important to make distinctions between the two groups since they wear different personal protective equipment (PPE) as was mentioned previously. Thus, the tenability limits for both groups of these parameters differ.

Unlike some tenability analyses previously performed in tunnels in which some limits are determined for certain time of exposure (short-term exposure limits (STEL)), in this study fires were classified using them as ceiling limits as also recommended by Gehandler et al. [33]. It has been observed during real mine fires and numerical simulations that when these parameters reach numbers close to the limits, it is almost a certainty that they will keep increasing if the fire is not attacked. Thus, STEL can be used as ceiling limit. Furthermore, considering the accessibility of underground coal mines and the potential remote location of fires it seems appropriate to have this cautious position. Table 2.1 shows the tenability limits proposed in this study for the FRG as well as the SRG. The exposure limits for combustion gases were obtained from the National Institute for Occupational Safety and Health (NIOSH) and Occupational Safety and Health Administration (OSHA). The tenability limits for CO, CO₂, and O₂ were 200 ppm, 3% and 19.5%, respectively. Note that the values of limits for CO and O₂ are already set as ceiling limits by NIOSH and OSHA [80].

The temperature and radiant heat limits for the FRG and the SRG proposed are the ones recommended by NFPA [78] and Haghghat [39]. It has been evidenced that inhaled sat-

Table 2.1: Tenable limits used for the FRG and the SRG.

Parameter	First responders' group (FRG)	Second responders' group (SRG)
CO ₂ (%)	<3	-
CO (ppm)	<200	-
O ₂ (%)	>19.5	-
Heat flux (kW/m ²)	<2.5	<5.0
Temperature (°C)	<60	<100
Visibility (m)	>20	>5

urated water vapor by barefaced personnel with temperatures greater than 60°C produce adverse effects in the respiratory tract [66]. For this reason, 60°C was used as ceiling limit for the FRG. For the SRG wearing turnout gear, a limit of 100°C was used as proposed in Haghighat's work. Although NFPA says that radiation level of 2.5 kW/m² and 5 kW/m² can be withstood by the FRG and the SRG for around 7 minutes, respectively, in this study these values were considered ceiling limits due to the reason explained previously.

For purposes of this work, the visibility for the SRG was set to 5 m. Although visibility is the most subjective criteria, Gehandler et al. [33] proposed this visibility limit for firefighting personnel who knows the environment where the fire occurs. The visibility limit is usually determined based on the relationship between walking speed and visibility [31]. For the FRG the visibility limit was set to 20 m following a more conservative approach since this group is composed of barefaced miners. A maximum visibility set to 30 m and optical coefficient (C) equals to 3 assuming light reflecting signals along the mine entry were used in FDS [72]. Explosibility was not considered in this study, however if fire firefighters observe or suspect an explosive atmosphere during an ongoing fire (e.g., methane concentration between 5-15% with an oxygen concentration between 15-20%), the scenario must be considered as not tenable immediately.

2.3.3 Identification of parameters with influence on the firefighting decision.

As mentioned previously, direct attack is preferred since it is possible to mitigate the hazard before it grows significantly. During direct attack firefighters approach the fire and position themselves approximately 5 m upwind of the fire [74]. Once in place, firefighters proceed to try and suppress the fire using water sprays or firefighting foam. This process is continued until the fire is suppressed or conditions grow untenable. Since mines use high airflows to mitigate particulates in the air, the upwind position is generally safe when a fire is small. However, larger fires can result in smoke and combustion gases traveling backward through the tunnel (towards the forced ventilation). This reversal of the flow of smoke within a tunnel is known as rollback or back-layering. When rollback occurs, the visibility and toxicity at the attack position can be affected, leading to untenable conditions.

The determination of parameters with direct influence on attack position conditions, and consequently on firefighting decision, lies in identifying parameters related to the rollback presence and the composition of the smoke when it occurs. The parameters that have direct influence on the presence and amount of backlayering are longitudinal air velocity, mine entry dimensions (height and width) as well as fire size and location [58, 59, 81, 99, 103, 108]. The parameters that influence the composition of rollback are related with the composition of the fuel(s) involved in the fire reaction, reaction efficiency, and oxygen availability. Combustion products and smoke constituents can be determined by the calculation of post combustion yields of carbon dioxide Y_{CO_2} , carbon monoxide Y_{CO} , and soot Y_{Soot} . The post combustion yields of Y_{CO_2} , Y_{CO} and Y_{Soot} are defined as the fraction of fuel mass converted into carbon dioxide, carbon monoxide, and smoke particulate, respectively [72].

The parameters that influence temperature and radiation are the fire size, radiative fraction,

Table 2.2: Parameters with direct influence on conditions at the attack position, and consequently on firefighting decision. Parameters are related to the tenability parameters affected

Visibility/Toxicity		Temperature/Radiation
Rollback presence/amount	Rollback composition	
Entry Height	Fuel composition	Fire growth rate
Entry width	Yco	Time
Longitudinal air velocity	Ysoot	Heat of combustion
Fire size and location		Fire size
Fire growth rate		
Time		

and the heat of combustion. It is noteworthy that the elapsed time after fire ignition and fire growth rate are important variables to be considered since fire size is dependent on these two variables. Table 2.2 shows the parameters with direct influence on the attack position. In Table 2.2 parameters are related to the tenability parameters affected. For the elaboration of the data-driven approach in this study most of the parameters shown in Table 2.2 were varied to test the performance of this approach under multiple scenarios with different outcomes as will be shown in Section 2.3.6. Fire location and parameters related to the fuel properties, composition, and radiative fraction were not varied since a fixed fire position and the same fuel were used for all scenarios. However, the impacts of fire location and unknown fuel type on the model performance were determined and discussed in Section 2.4.2.

2.3.4 Identification of parameters available during underground coal mine fires

In order to design the machine learning model, it is important to identify all the information which is measurable and available on-site during ongoing underground coal mine fires. Title 30 CFR 75.351(e)(f)(h) requires the monitoring of carbon monoxide by an atmospheric mon-

itoring system (AMS) or CO system at key locations in underground coal mines such as belt and return entries, working faces, electrical installation locations, and primary escapeways [101]. An AMS is defined as a network consisting of hardware and software capable of measuring atmospheric parameters and transmitting the measurements to a designated surface location (Title 30 CFR § 75.301). An AMS is basically a CO system with additional sensors. Based on the mining regulation, it can be stated that CO concentration is measured in real time at different mine locations and transmitted to surface locations in all US underground coal mines.

The percentages of usage of different sensor types along belt entries in underground coal mines in the US are shown in Table 2.3. These statistics were collected in a survey carried out in 235 US producing coal mines performed by Rowland et al. [85] with the help of the MSHA district office. Results of this survey agree with the statement that CO sensors are used in all US underground coal mines at required locations such as belt entries. While many underground coal mines include additional measurements in their AMS, such as air velocity, temperature, and species concentrations (O_2 , NO , H_2), these sensors were not considered in this work since they are not required by Title 30 CFR and not available in the majority of mines.

Based on this analysis, CO concentration was selected as one of the input parameters of the data-driven approach. In addition to CO concentration, there are many known operating parameters that can impact the behavior of a mine fire. For example, mine entry dimensions, time elapsed after fire detection, and nominal longitudinal air velocity are all known factors since they are part of the mine's operating procedures. These additional parameters were used along with CO concentration as input parameters to the machine learning model. In summary, CO concentration, air velocity, mine entry dimensions, and time elapsed after fire detection are the parameters used as inputs for the data driven approach proposed in

Table 2.3: Percentages and numbers of different sensors used in underground coal mines. This data was collected in a survey carried out in 235 US producing coal mines performed by [85] with the help of the MSHA district office

Parameter	Mines (%)	Min sensors	Max num sensors
CO	100	2	300
CH ₄	17	1	20
O ₂	6	1	20
Smoke	2	1	14
Air velocity	9	1	20
Thermal	2	4	191
NO	1	1	3
H ₂	2	1	3

this work due their measurability and availability in underground coal mines. A potential technology for continuous and distributed sensing of gases which could contribute to the data collection during mine fires is presented in [Appendix A](#)

2.3.5 Definition of the scope of the fire classification

The possible decisions that firefighters can make during ongoing mine fire scenarios are listed in [Section 2.3.1](#). The fire classification could consider all possible decisions. However, the scope of the fire classification must be defined based on the type and location of data available for training and testing the data-driven approach. As will be shown and discussed later in [Section 2.3.6](#), the data generated from numerical simulations can be divided into two types: spatial-temporal type and averaged type. The spatial-temporal data provides the atmospheric conditions parameters with high spatial and temporal resolution. This data type is generated using CFD simulations. However, the calculation time and computational cost makes CFD simulations prohibitive for large domains such as entire mine sections. For this reason, the spatial-temporal data is commonly available near the fire. The averaged data type gives the atmospheric conditions parameters with low spatial resolution but at a

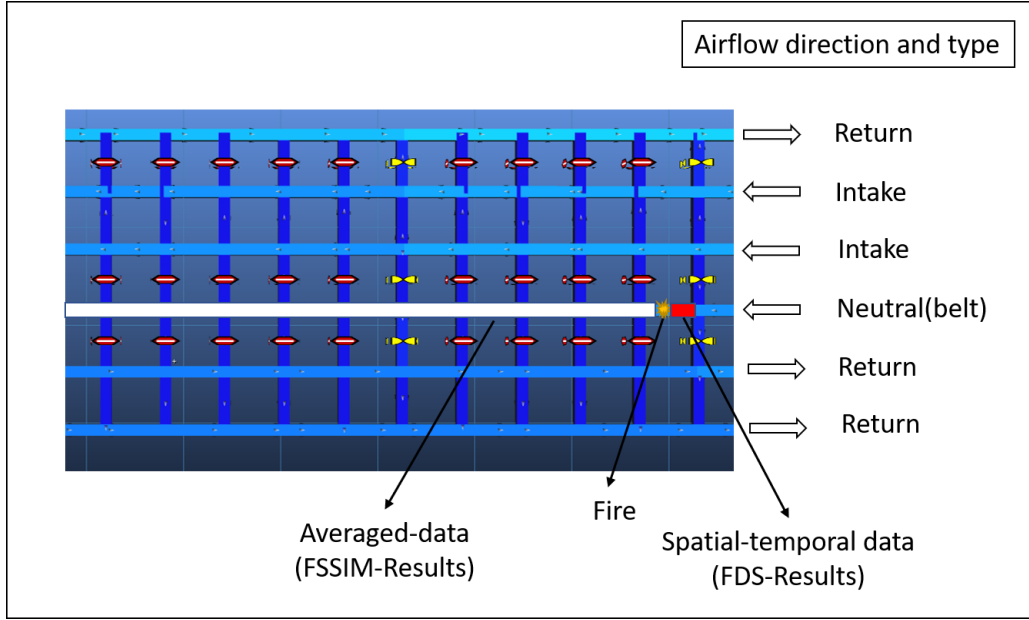


Figure 2.3: Fire and data available locations in a flat and straight mine entry for the proposed data-driven approach (top view).

lower computational cost and time. Thus, this data type is available for larger mine sections generated from zone/network fire models.

Due to its spatial resolution that allows for a precise and detailed evaluation of conditions, spatial-temporal data was generated in the fire proximity to determine the tenability at the attack position. On the other hand, averaged data was used to determine the CO concentrations downwind from the fire. Figure 2.3 shows the locations of each data type used for the construction of the data-driven approach in this study.

Based on the locations of the data available, the scope of the data-driven approach is restricted to recommend three main decisions for both groups as shown in Figure 2.4. The data-driven approach can recommend direct attack, evacuation, and evaluation. In addition, it can determine when conditions are about to become completely untenable for direct fire-fighting for any groups. For this reason, the classification suggested in this study proposes four different fire classes in which each one is associated with recommended decisions and

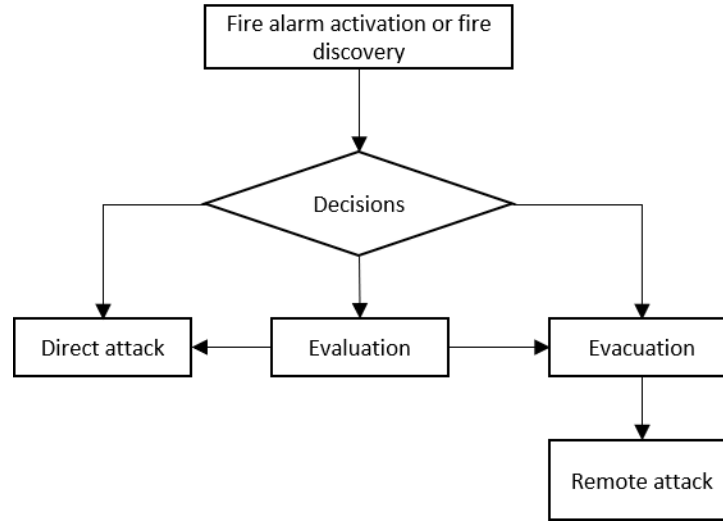


Figure 2.4: Sketch of the fire classification scope proposed in this study.

a description. The four fire classes are shown and described in Table 2.4. A fire Class I refers to a scenario where the atmospheric conditions upwind from the fire are tenable to approach and carry out direct attack by the FRG and the SRG. A fire Class I indicates that none of the tenability limits has been exceeded. Good conditions for a sufficient duration are guaranteed for the SRG. Fire Class II is a scenario in which the condition upwind of the fire is only tenable for the SRG. At least one tenability limit for the FRG has been exceeded, thereby the FRG evacuation is highly recommended. Furthermore, a fire Class II is used to recommend to the SRG an evaluation of the situation since there is already backlayering and conditions could get worse in minutes. In this case, parameters such as distance between fire and the SRG location as well as travel and approach times should be considered during evaluation. A fire Class III indicates that tenable conditions are guaranteed for no longer than 30 seconds for any groups. Thus, if the SRG members are not at the attack position, it is recommended to select remote attack instead of approaching for direct attack. In addition, if the scenario is classified as Class III while SRG is directly attacking the fire, evacuation is highly recommended because the attack is being ineffective. Finally, a fire Class IV is a scenario in which conditions are not tenable for any of the groups, since at least one of the

tenability limits for the SRG has been exceeded. Evacuation would have been previously performed, and remote attack from other sections or from the surface is recommended.

2.3.6 Data generation

As previously mentioned, the data-driven model was designed to classify fires in a straight and flat mine entry. This geometry is common on most of underground coal mines in the US and around the world where fires such as conveyor belt, mobile equipment (shuttle cars, scoops, railrunners, etc.), and coal fires produced by malfunctioning belts take place [20]. The data of fire scenarios in this geometry used to train and test the ANN of the data-driven approach was collected from numerical simulations. Before providing more details about the numerical models and data types used, it is important to mention that a data-driven approach as the one proposed in this study can also be constructed using experimental data coming from experiments or a combination of numerical and experimental results. The experimental data is mostly desirable since it contains all physics of the problem [41]. However, fire experimental studies are restricted or prohibited in active underground coal mines and these studies in fire laboratories are very limited to the facility size, fire sizes, materials involved, etc.

As previously mentioned, the data used in this study can be classified into two types: spatial-temporal data and data averaged. The spatial-temporal data was generated using Fire Dynamic Simulator (FDS) Version 6.7.1 developed by NIST [71]. The averaged data was generated from a zone fire model (ZFM) called Fire and Smoke Simulator (FSSIM) [28]. In the following subsections details about the data generation using both models are discussed.

Table 2.4: Recommended decisions and description for each proposed fire class

Fire Class	Decisions recommended	Description
I	Both groups can approach the fire location and perform direct attack.	Conditions at the attack position are adequate for both groups. None of the tenability limits have been exceeded.
II	Only the SRG can approach and perform direct attack. However, evaluation is recommended, and the following aspects should be considered by the SRG:	Conditions upwind from the fire are only tenable for the SRG.
	Fire location. SRG position. Approach time.	At least one tenability limit for the FRG has been exceeded.
	Section evacuation for the FRG.	Warning for the SRG since the conditions can get worse in minutes due to rollback
III	If the SRG members are not at the attack position, it is recommended to select remote attack.	Tenable conditions are guaranteed for no longer than 30 seconds for the SRG
	If SRG is directly attacking the fire, and scenario becomes class III, evacuation is highly recommended.	
IV	Evacuation would have been previously performed, and remote attack from other sections or from the surface is recommended.	Conditions upwind from the fire are not tenable for the SRG.
		At least one tenability limit for the SRG has been exceeded.

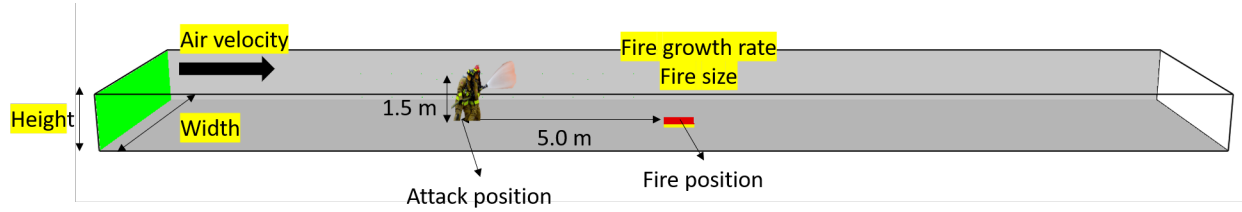


Figure 2.5: FDS geometry in which parameters varied in simulations are highlighted.

Table 2.5: Range of each parameter in study

Parameter	Range
Air velocity	0.5-2.0 m/s
Fire size	500-7000 kW
Fire growth rate	0.01172-0.1876 s ⁻¹
Height	1.8-2.8 m
Width	5.0-7.0 m

CFD data generation

CFD simulations were carried out to determine the atmospheric conditions at an attack position 5.0 meters away upwind from the fire using FDS. FDS is a 3-D large-eddy simulation model that solves the governing equations of mass, momentum, energy, and species conservation equations.

The geometry used for FDS simulations is shown in Figure 2.5. The range of parameters varied in numerical simulations are shown in Table 2.5. Air velocity range was determined based on the mining regulation (Title 30 CFR 75.500)[101]. Geometric parameters range

Table 2.6: Material used to simulate the fire. Heat of combustion (ΔH_c), CO, soot, and CO₂ yields (Y_{CO} , Y_{CO} , CO₂)

Material	Chemical Formula	ΔH_c (kJ/kg)	Y_{CO}	Y_{SOOT}	Y_{CO_2}
Polyurethane	C ₃ H ₈ N ₂ O	25300	0.02775	0.1875	1.5325

(tunnel height and width) were determined based on the ranges of standard dimensions of underground coal mines in the US. The lower and upper limits of fire growth rate refer to the standard medium and ultrafast growth rates. Fire size range was determined based on previous fire size estimations in underground coal mines [8, 17, 39, 113]. The grid resolution was set to 0.1 m along each axis of the domain for each simulation to reduce the calculation time as well as the computational cost per simulation. Although this grid resolution does not fully resolve the source fire for sizes between 0 and 1000 kW, the predictions were adequate for exploratory analysis in which the interest was on classifying fires from available input parameters during active fires rather than comparing to experimental results.

The parameter values for each unique scenario were obtained using simple random sampling from uniform distribution in which each value has the same probability of being chosen during the sampling process. 500 unique scenarios were simulated. The simulation time for each scenario varied depending on the fire size and growth rate. Each simulation was programmed to last until quasi-steady state of the fire was reached. They were maintained at the maximum fire size for some time until the values predicted by FDS such as gas concentrations, visibility, heat flux, and temperature were constant. The fire was located at the center of the tunnel with a height of 0.1 m from the floor. The fire growth rate was determined following the t-squared approach in which the fire size at any time (t) is calculated using Equation 2.1. Previous research has shown that common mines fires in elongated mine entries such as belt fires, coal fires, and mobile equipment can be represented using the t-square approach [44, 110, 111, 113]. Flexible polyurethane foam properties shown in Table 2.6 were used to simulate the fire in the mine entry [96].

$$HRR(t) = \alpha t^2 \quad (2.1)$$

In the above equation, HRR is the fire size at time (t) and α is the fire growth rate that it is defined as shown in Equation 2.2. As previously mentioned, the lower and upper limits of the fire growth rate range refer to the standard medium and ultrafast growth rates, respectively.

$$\alpha = \frac{HRR_{max}}{t_{max}^2} \quad (2.2)$$

In the above equation, HRR_{max} is the maximum fire size reached at a time t_{max} .

The parameters mentioned in Section 2.3.2 which allows for the evaluation of atmospheric conditions for firefighters shown in Table 2.3 were determined during the simulations. The value of each parameter was calculated at intervals of 1 second at the attack position 5 meters away upwind from the fire and at a height of 1.5 m as shown in Figure 2.5. It was assumed that the FRG and the SRG would crouch when they approach and attack the fire with the objective to stay below the smoke layer as also was assumed by Haghighat et al. [39]. Thus, a height of 1.5 m seems a reasonable height for the face position of the firefighters.

Zone fire model data generation

In order to determine the CO concentration evolution downwind from the fire for each scenario, a ZFM called Fire and Smoke Simulator (FSSIM) was used. FSSIM is also referred to as a network fire model or zero dimensional model. A ZFM such as FSSIM is recommended to be used for the determination of low resolution predictions over large domains to reduce calculation time and computational cost. In FSSIM each control volume or compartment is represented as single node. Junctions that represent flow paths are defined between nodes in which heat, mass and momentum transfer occur. The approach of just having one node per control volume minimizes the computational cost and time allowing for predictions of smoke spread in larger domains. FSSIM solves the 1-D conservation equations for mass,

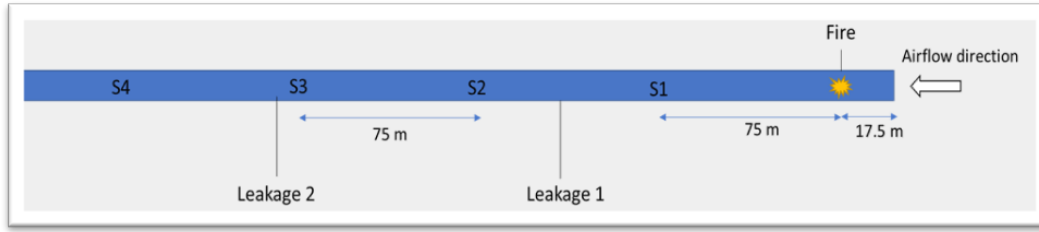


Figure 2.6: Geometry used in FSSIM, location of sensor stations, fire, and leakages (top view).

momentum and energy [28]. In the ZFM it is assumed that properties such as temperature, density and chemical species take constant values through each zone.

The 500 scenarios simulated in FDS were also simulated in FSSIM using the same input parameters and fuel properties shown in Table 2.5 and Table 2.6, respectively. FSSIM simulations were used to determine the CO concentrations 300 m downwind from the fire in each scenario. The downwind CO concentration was determined at intervals of 1 second at four different sensor stations with a spacing of 75 m as shown in Figure 2.6. The four CO concentrations detected at the sensor stations at each time step were used as input parameters in the data-driven approach. The fire was located 17.5 m away from the inlet. The length of the geometry used in FSSIM was 400 m split into 80 compartments. Thus, the length of each compartment was 5 m. The height and width depended on the mine entry dimensions of each scenario. Finally, two air leakages along the tunnel were considered based on the location of crosscuts downwind from the fire. The airflow quantities at leakages points were calculated based on measurements of airflows in a partner mine.

2.3.7 Data preparation

The methodology of the data preparation is summarized in the sketch shown in Figure 2.7. FDS simulation results were linked with FSSIM results for each scenario. The results of the

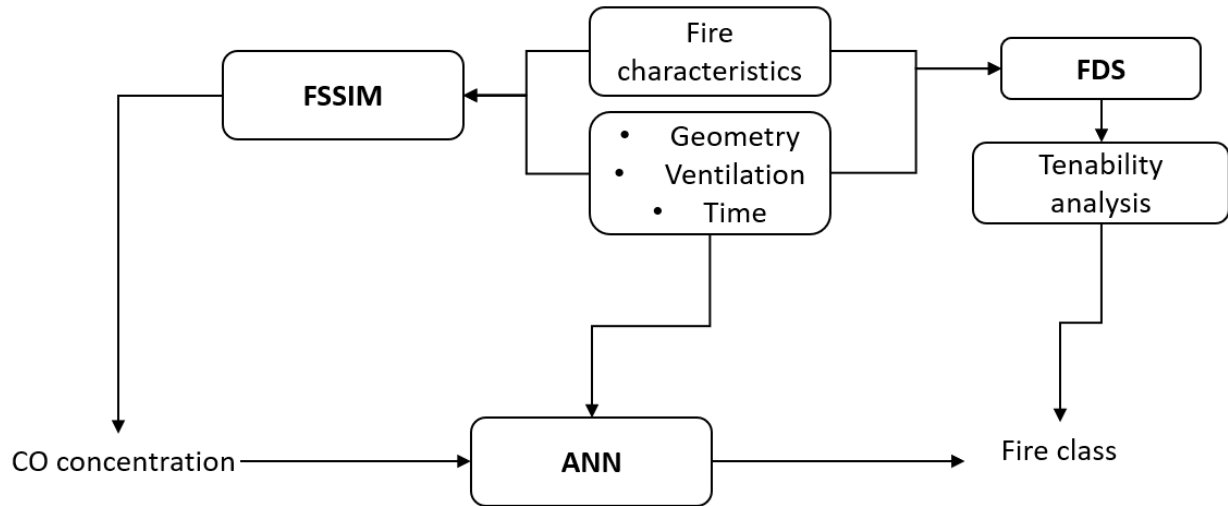


Figure 2.7: Sketch of the methodology used during data preparation.

Table 2.7: Some FDS and FSSIM simulation results of Scenario A after linking

Scen.	Time step	FDS/FSSIM		FDS		FSSIM	Class IV time (s)	Resultant Time (s)
		Fire size (kW)	Time (s)	Temp. (°C)	Vis. (m)	CO (ppm)		
A	194	450	194	20	30	5	466	272
A	381	1741	381	26	19	26	466	85
A	460	2549	460	40	6.2	40	466	6
A	487	2844	487	47	2.6	46	466	-21

tenability parameters at the attack position for each time step calculated in FDS (temperature, visibility, radiation, and gas concentrations) were linked with the CO concentrations downwind from the fire predicted in FSSIM. It is noteworthy that the fire size for each time step predicted by both models was the same since simulations parameters, such as the maximum fire size and fire growth rate, were identical in FDS and FSSIM. Results of the linking process of four different time steps of scenario A are shown in Table 2.7 and Table 2.8. The column FDS/FSSIM in Table 2.7 shows the parameters in common for both models. At these four time steps (194 s, 381 s, 460 s, and 487 s), the fire sizes predicted were 450 kW, 1741 kW, 2549 kW, and 2844 kW in both models, allowing for linking between conditions at the attack position predicted by FDS and CO concentrations downwind from the fire predicted by FSSIM. For the purpose of simplicity, only one value of CO concentrations is shown in Table 2.7, whereas the values of combustion gas concentrations and radiation were omitted. Next, the fire Class IV time defined as the time when conditions start to be completely untenable was determined for each scenario. The fire class IV time was determined to be 466 s in Scenario A, as shown in Table 2.7. Then, each time step was subtracted from the fire Class IV time for each scenario. This resultant time was the remaining time for which conditions become completely untenable, allowing for classification of fire Class III. A Negative resultant time means that conditions have been untenable during this time. Finally, the other time steps were classified based on the tenability limits proposed in Table 2.1. Final results of data preparation of these time steps are shown in Table 2.8.

2.3.8 Elaboration of the ANN

Hyperparameters tuning and cross validation were implemented for the elaboration of the ANN model. Hyperparameters shown in Table 2.9 were tested to select the most optimal arguments for the predictive model. Cross validation (CV) was used for models' evaluation

Table 2.8: Final results of data preparation for some time steps of Scenario A shown in Table 7

Scen.		Inputs			Output
	Time	v (m/s)	Dim (height x width) (mxm)	CO (ppm)	Class
A	194	1.4	2.8 x 6.2	5	I
A	381	1.4	2.8 x 6.2	26	II
A	460	1.4	2.8 x 6.2	40	III
A	487	1.4	2.8 x 6.2	46	IV

during hyperparameters tuning. In this study, CV consists of splitting the training dataset into three subsets. Two subsets were used for training while the third one for testing. Then, the subsets were switched to repeat the process. An average value of the three metrics of each model was used for evaluation. F1 score weighted average calculated using Equation 2.6 was used as the evaluation metric.

It is noteworthy that the input and output layers consisted of 8 and 4 units for any hyperparameters combination, respectively. As previously discussed, inputs were known and available parameters during ongoing fire scenarios. Units in the output layer were associated with the four fire classes, allowing for the determination of the probability of each class. The output unit with the highest value was selected as the class predicted by the model. One-hot encoding process [35] and the “SoftMax” activation function were used in the output layer to ensure the output values were in the range of 0 and 1. Network architectures were created using Keras, a high-level neural network library built-in Python that runs on top of TensorFlow, an open-sourced end-to-end platform [1, 15]. Models were trained for 1000 cycles with a batch size of 50 samples and all weights, as well as biases, were initialized from a normal distribution with zero mean and 10^{-2} standard deviation.

The first hyperparameters tested and selected were the number of units per layer and number

Table 2.9: Hyperparameters tested for the selection of the most optimal arguments for the predictive model

Hyperparameter	Option 1	Option 2	Option 3
Hidden layer(s)	1	2	3
Units per hidden layer	4	8	-
Activation Function	ReLu	Sigmoid	-
Dropout	0	0.05	-
Optimizer	Adam	SGD	-
Loss	Categorical cross entropy (CCE)	Kullback Leibler divergence (KLD)	-
Learning Rate (LR)	0.01	0.1	-

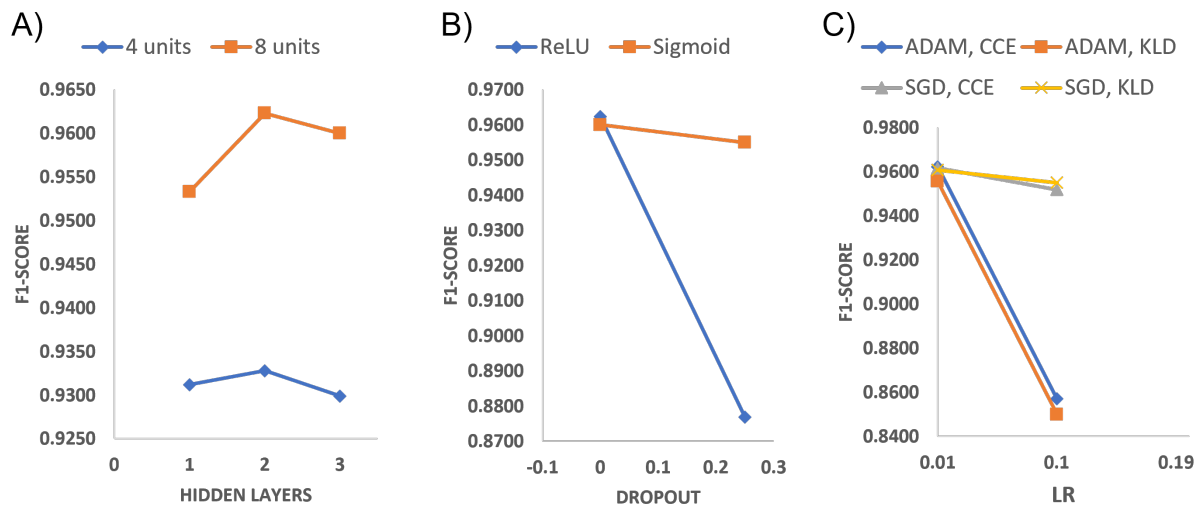


Figure 2.8: CV results

of hidden layers. CV results for this first evaluation are shown in Figure 2.8A. The best F1 score was obtained when the number of hidden layers was 2 and the number of units per hidden layer was 8. The second hyperparameters selected were activation function in the hidden layers and dropout regularization. The highest F1 score was obtained when ReLU and Sigmoid activation functions were used with a dropout regularization equal to zero as shown in Figure 2.8B. It was decided to use ReLU since Sigmoid could vanish the gradient during the learning process. In addition, it can be said that regularization was causing underfitting in the models. Big amount of data and small amount of features, as used in this paper, allow for a generalized model on unseen data, as shown in Section 2.4, without using regularization. Finally, learning rate (LR), optimizer, and loss function were evaluated. Results shown in Figure 2.8C indicate that as long as a LR of 0.01 is used with any of the two optimizers and loss functions evaluated, the model exhibits good prediction performance. Table 2.10 shows the F1 score for each model evaluated during CV. The ANN with 2 hidden layers, 8 units per hidden layer, ReLU activation function, LR of 0.01, Adam optimizer, and CCE loss function obtained the maximum F1 score equal to 0.9623. Thus, these hyperparameters were selected for the data-driven model proposed in this study. The ANN architecture used is shown in Figure 2.8. It is worth mentioning that two hidden layers configuration can represent any arbitrary decision accuracy with rational activation functions and can approximate any smooth mapping to any accuracy [35].

2.4 Results and discussion

The results of the 500 simulations in FDS and FSSIM were linked and processed to generate the samples for the ANN as detailed in Section 2.3.7. This indicates that a fire class was assigned to each time step of every simulation through the comparison between the tenability

Table 2.10: CV F1-scores for different hyperparameters combination during CV

Hidden layers/ units	Activation	Dropout	Loss	Optimizer	Learn rate	CV F1-Score
[4]	ReLu	0	CCE	Adam	0.01	0.9312
[8]	ReLu	0	CCE	Adam	0.01	0.9533
[4-4]	ReLu	0	CCE	Adam	0.01	0.9328
[8-8]	ReLu	0	CCE	Adam	0.01	0.9623
[4-4-4]	ReLu	0	CCE	Adam	0.01	0.9299
[8-8-8]	ReLu	0	CCE	Adam	0.01	0.9600
[8-8]	ReLu	0.25	CCE	Adam	0.01	0.8768
[8-8]	Sigmoid	0	CCE	Adam	0.01	0.9600
[8-8]	Sigmoid	0.25	CCE	Adam	0.01	0.9550
[8-8]	ReLu	0	CCE	Adam	0.1	0.8570
[8-8]	ReLu	0	CCE	SGD	0.01	0.9617
[8-8]	ReLu	0	CCE	SGD	0.1	0.9519
[8-8]	ReLu	0	KLD	Adam	0.01	0.9557
[8-8]	ReLu	0	KLD	Adam	0.1	0.7981
[8-8]	ReLu	0	KLD	SGD	0.01	0.9608
[8-8]	ReLu	0	KLD	SGD	0.1	0.9551

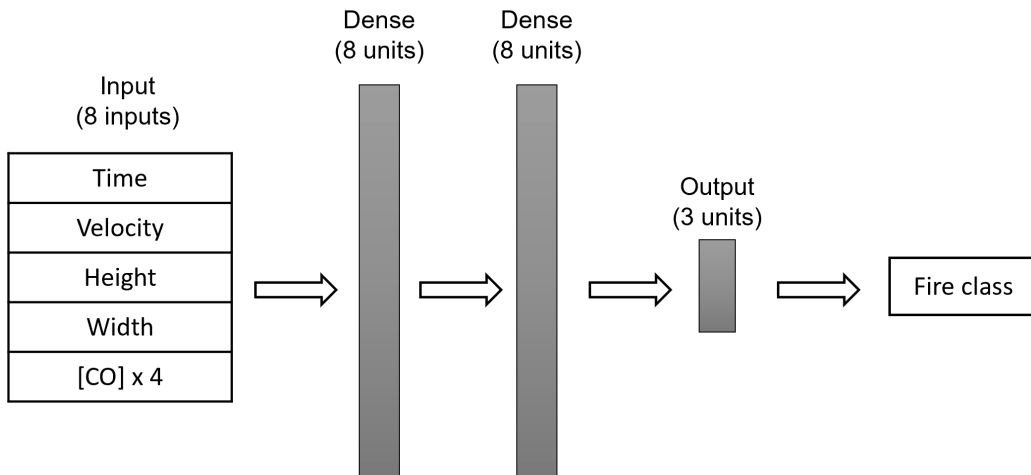


Figure 2.9: ANN architecture

limits and FDS results at the attack position. The total collected number of samples in the dataset for training and testing the ANN was 110,695 which were randomly split into two, with 80 percent for training and 20 percent for testing the ANN. Alwosheel et al. [3] advise to use a minimum of sample size equal to fifty times the number of weights present in the ANN. The ANN used in this study has 171 weights which suggests that at least 8550 samples are required based on Alwosheel's recommendation. This indicates that the dataset obtained from the 500 simulations is big enough for the elaboration of the data-driven approach.

It is noteworthy that the FDS results such as visibility had large fluctuations inherent to the turbulent flow at the attack position as shown in Figure 2.11. This could result in poor performance of the ANN. For this reason, FDS results were processed applying an average filter with a window of 15 seconds before linking. The difference of processed and raw results of visibility for a Scenario A is shown in Figure 2.11. The proportion of each fire class (defined in Table 2.4) in the entire dataset is shown in Figure 2.10, which shows that the proportions of samples Class I and Class IV are much greater than Class II and III samples. This can be explained due to the short time of scenarios classified as Class II and III. It was seen that once the rollback reaches the attack position, the values of the tenability parameters quickly exceed their limits as shown in Figure 2.11 for processed visibility. In addition, it is important to mention that scenarios can be only classified as Class III for 30 seconds before the conditions become completely untenable. Figure 2.12 shows the true fire class evolution in Scenario A. It shows that the total time for Class III is the shortest one.

In order to evaluate the performance of the ANN, four metrics were used. The first metric was Accuracy (A) defined as the proportion of samples correctly classified among the total number of samples examined as shown in Equation 2.3. The second and third metrics were the Precision (P) and Sensitivity (S) calculated for each fire class using Equations 2.4 and 2.5, respectively. These two metrics were calculated to evaluate the performance of the ANN

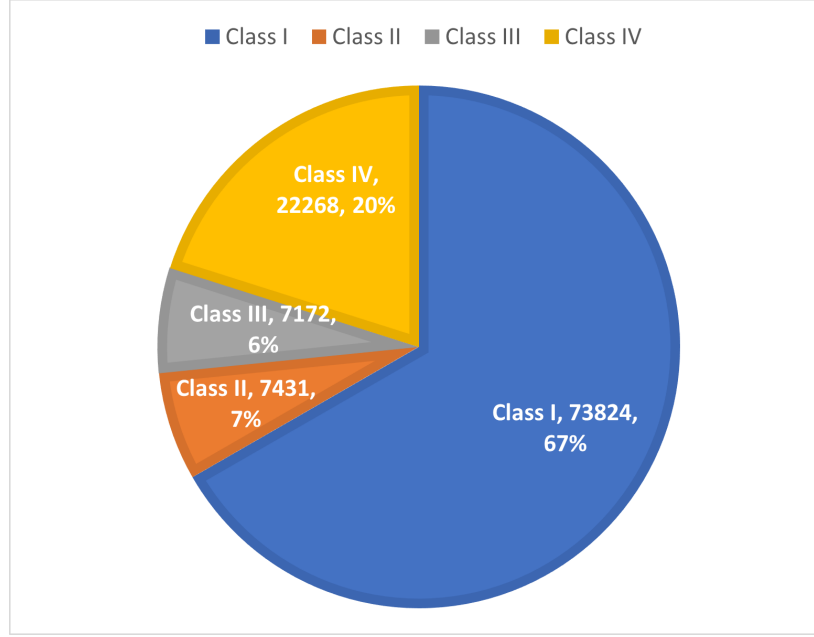


Figure 2.10: Number of samples and percentages per fire class.

for each fire class since fire classes do not have the same level of occurrence in the dataset as mentioned previously. The precision is defined as the fraction of samples predicted as a respective class truly identified. The precision is seen as a measure of commission errors (predicting a class when it should have been other class) . The sensitivity measures the fraction of samples of a respective class which are correctly classified. The sensitivity is a measure of omission errors (predicting other class when it should have been the respective class) [35]. The last metric was F-1 score defined as the harmonic mean of P and S determined using Equation 2.6.

$$A = \frac{\sum_{c=1}^3 t^c}{N} \quad (2.3)$$

$$P_c = \frac{t^c}{t^c + \sum_{x=1}^3 f_c^x} \quad (2.4)$$

Table 2.11: Confusion Matrix

		True/Actual			
Predicted	Class	I	II	III	IV
	I	t^I	f_{II}^I	f_{III}^I	f_{IV}^I
	II	f_{II}^I	t^{II}	f_{III}^{II}	f_{IV}^{II}
	III	f_{III}^I	f_{III}^{II}	t^{III}	f_{III}^{IV}
	IV	f_{IV}^I	f_{IV}^{II}	f_{IV}^{III}	t^{IV}

$$S_c = \frac{t^c}{t^c + \sum_{x=1}^3 f_x^c} \quad (2.5)$$

$$F_{1-c} = 2 \frac{P_c + S_c}{P_c S_c} \quad (2.6)$$

In the above equations, A is accuracy, P_c , S_c , and F_{1-c} are the precision, sensitivity and F_1 score of Class C , respectively. t^c is the number of samples correctly classified as class C , f_x^c is the number of samples predicted as class x being Class C , and, f_c^x is the number of samples predicted as class C being Class x . The confusion matrix shown in Table 2.11 consists of the parameters included in Equations 2.3-2.5. In Table 2.11 is shown that t_I, t_{II} , and t_{III} are located at the intersection between the row of the predicted class and the column of the true/actual Class indicating the number of samples correctly classified. In the other cases such as f_{II}^I , its location is at the row of predicted Class II under the column of true/actual Class I or in simple words number of samples predicted as Class II being Class I.

It is important to mention that the data was shuffled before being split into training and testing. This assured that training and testing data were representative of the overall distribution of the data resulting in a more general model. Confusion matrices for training and testing data are shown in Table 2.12 and Table 2.13. The values of precision, sensitivity

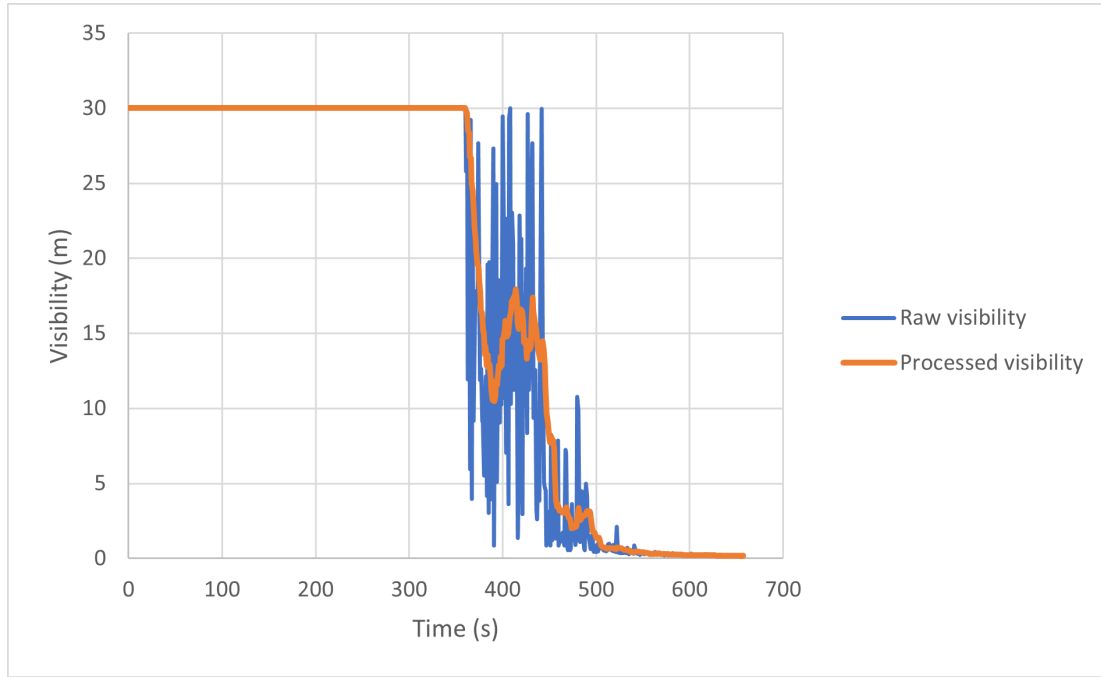


Figure 2.11: Raw and processed visibility for scenario A.

Table 2.12: Complete confusion matrix for training dataset

		True/Actual			
Predicted	Class	I	II	III	IV
	I	58545	577	41	7
	II	703	4594	588	10
	III	37	523	4919	270
	III	12	0	373	17357

Table 2.13: Complete confusion matrix for testing dataset

		True/Actual			
Predicted	Class	I	II	III	IV
	I	14504	139	10	1
	II	184	1223	128	1
	III	6	153	1205	59
	III	3	0	79	4444

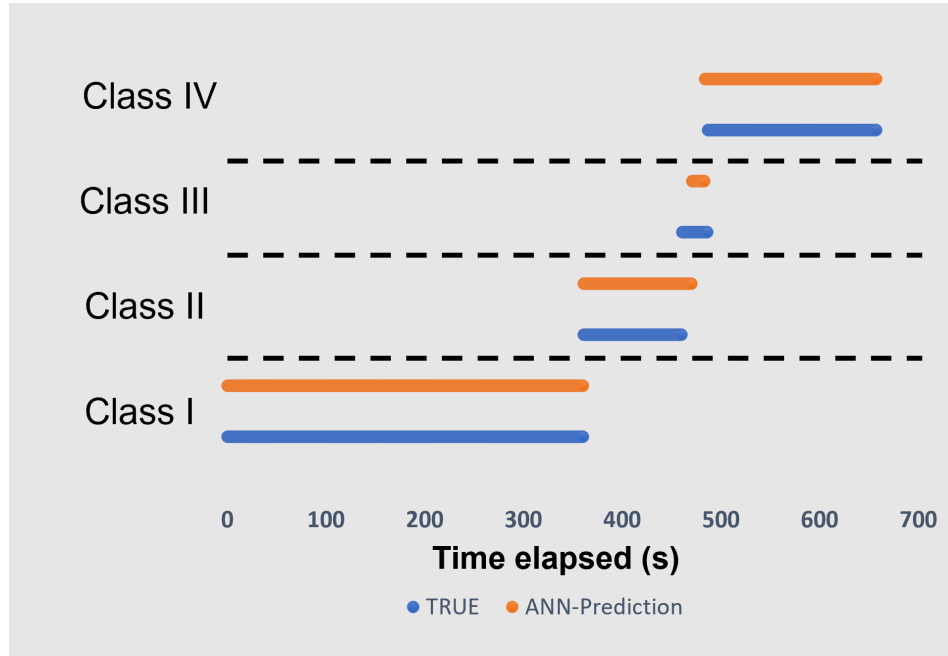


Figure 2.12: True and predicted fire class evolution in Scenario A. Blue and orange lines represent the true and predicted time elapsed on classes shown on the vertical axis, respectively.

and F_1 for training and testing data are shown in Table 2.14 and Table 2.15, respectively. Furthermore, the macro average and weighted average of precision, sensitivity and F_1 score are also shown in these Tables. Values of these performance metrics are between 0 and 1 in which values near 1 represents a better classification performance of the ANN. The statistical measures of the performance shown in Table 2.14 and Table 2.15 indicate the overall accuracy and weighted average F_1 score of the ANN are around 0.970 for training and testing data. Much of the classification error can be attributed to the performance of the ANN classifying fire Class II and Class III as shown in Table 2.12, Table 2.13, and evidenced in low F_1 scores for these two classes around 0.80 for both training and testing data. They are the lowest values when compared with F_1 scores of Classes I and IV.

The relative low performance for Class II and III can be explained with two factors. The first factor is related to the evolution of the conditions at the attack position is not immedi-

Table 2.14: Performance matrix for training dataset

Class	Precision	Sensitivity	F1-score	No of samples
I	0.99	0.99	0.99	59170
II	0.81	0.80	0.80	5895
III	0.83	0.86	0.84	5749
IV	0.98	0.98	0.98	17742
Accuracy			0.97	88556
Macro avg	0.90	0.90	0.90	88556
Weighted avg	0.96	0.970	0.96	88556

Table 2.15: Performance matrix for testing dataset

Class	Precision	Sensitivity	F1-score	No of samples
I	0.99	0.99	0.99	14654
II	0.81	0.80	0.80	1536
III	0.85	0.85	0.85	1423
III	0.99	0.98	0.98	4526
Accuracy			0.97	22139
Macro avg	0.91	0.90	0.91	22139
Weighted avg	0.97	0.97	0.97	22139

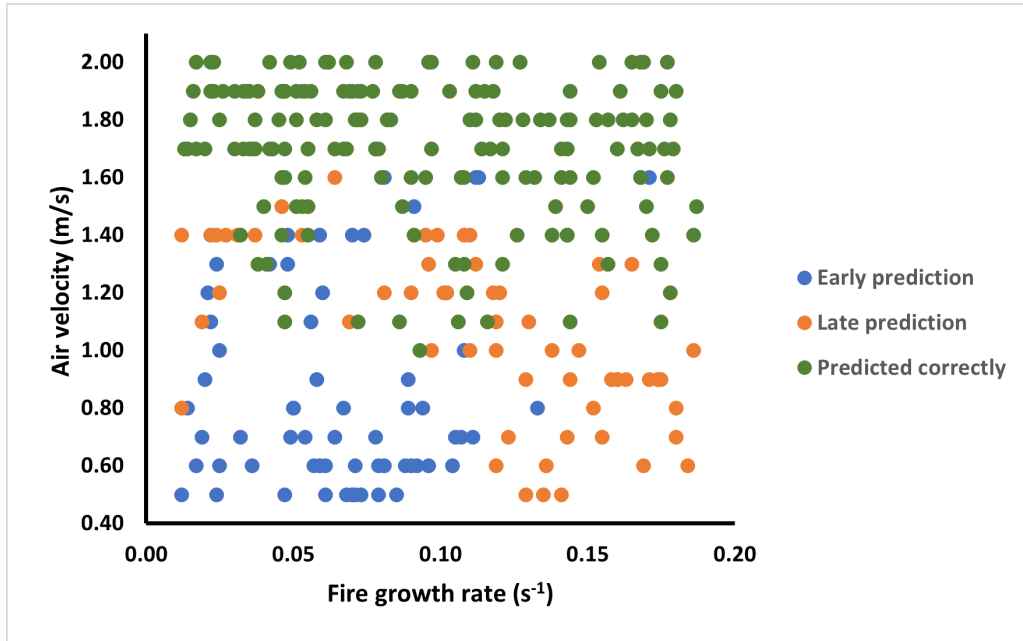


Figure 2.13: Scenarios that go through the three classes where fire classes changes were predicted early, late, and correctly.

ately reflected in the variation of the CO concentration downwind from the fire. Higher air velocities make the CO concentration travels faster downwind from the fire. Nonetheless, lower air velocities reduce the travel time of CO produced at the fire causing the ANN to misclassify fires when they just evolve to Class II and III. The timing of the ANN predicting fire class change for scenarios that go through the four classes are shown in Figure 2.13. Figure 2.13 shows the trend of the ANN to correctly classify fire class change in scenarios with higher air velocities. Scenarios with an air velocity greater than 1.6 m/s were classified correctly over time.

For scenarios with air velocity lower than 1.6 m/s the fire growth rate plays an important role in determining when the ANN predicts a fire class change. Figure 2.13 shows the trends in the ANN predictions for fire class change in these scenarios. When the fire growth rate is low the scenario times are longer , causing the ANN to anticipate a fire class change early because of the long time period elapsed. Conversely, in scenarios with a faster fire evolution

Table 2.16: Summary of ANN time gap predictions of fire Class change. Considering early predictions, late predictions, and all scenarios. Values correspond to mean and standard deviation.

tg_{I-II}^{early}	tg_{II-III}^{early}	tg_{III-IV}^{early}
-4.67 ± 7.23 s	-4.15 ± 4.48	-2.36 ± 3.02
tg_{I-II}^{late}	tg_{II-III}^{late}	tg_{III-IV}^{late}
3.72 ± 3.87 s	3.45 ± 3.40 s	2.61 ± 3.24 s
$\overline{tg}_{I-II}$	$\overline{tg}_{II-III}$	$\overline{tg}_{III-IV}$
0.17 ± 4.78 s	-0.085 ± 3.75 s	0.17 ± 2.55 s

(i.e., a higher growth rate) the ANN predicts the fire class change late due to the short time elapsed. This behavior is shown in Figure 2.12 for scenario A in which the true fire Class is II for 100 s, nevertheless the model classifies this scenario as Class II for 109 s. The network misses the true fire class for 9 s when fire becomes Class III. Also, the model anticipates the true fire Class for 2 s when scenario A becomes Class IV.

The second factor is related to the small number of samples of Class II and III due to the nature of the fire condition evolution and the time considered for fire Class III. It was seen that once the rollback was detected the conditions get worse quickly resulting in short times of scenarios classified as Class II, and consequently a fewer number of samples. This fact could provide less evidence to the ANN to identify fire Class II and III.

In order to determine the degree of accuracy of the ANN in terms of time, the time gap (tg_{x-y}) between the time of true fire class change and the time of class change predicted by the ANN was calculated using Equation 2.7. It is important to mention that the determination of the ANN accuracy in terms of time can provide a better estimation of the uncertainty of the data-driven model in fire class predictions.

$$tg_{x-y} = t_{NN_{x-y}} - t_{True_{x-y}} \quad (2.7)$$

In the above equation, $t_{True_{x-y}}$ is the true time at which the fire evolves from Class x to y determined by FDS results, and $t_{NN_{x-y}}$ is the predicted time by ANN at which the fire evolves from Class x to y.

Table 2.16 shows the mean and standard deviation of tg_{x-y} considering early (tg_{x-y}^{early}) and late (tg_{x-y}^{late}) predictions of fire class change (i.e. blue and orange points in Figure 2.13), respectively. It is noteworthy that a negative number indicates that the ANN anticipates the fire class change and a positive number indicates that ANN delays the fire class change. In the similar way, the mean and standard deviation of tg_{x-y} including all scenarios are shown in Table 2.16. Based on these statistics, it can be stated that 95% of ANN predictions for fire class change should have a time gap within ± 9 s of the true fire class change. This value related to the ANN accuracy in terms of time highlights the capability of the proposed approach to classify fires in real time during ongoing underground coal mine fires only using available and measurable parameters.

2.4.1 Impact of fire location on data-driven model performance

In order to determine the fire location impact on the data-driven model accuracy, 200 additional scenarios were simulated. In these additional scenarios, parameters shown in Table 2.5 and fire location were varied simultaneously. Three fire positions, such as center, left, and right were varied. Additionally, the fire height (Z) was varied between 0.4 m and 1.7 m from the floor. Figure 2.14 shows the fire location variation in the tunnel. The same geometry, grid resolution, fuel, sampling process, fire models result post-processing, and classification criteria used in the simulations for the elaboration of the data-driven model were imple-

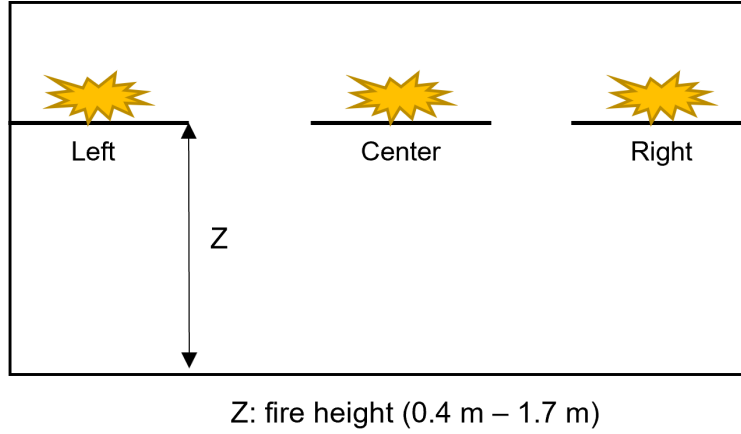


Figure 2.14: Fire locations in the mine tunnel cross section (front view)

Table 2.17: Summary of performance of ANN time gap predictions of fire class change in term of time for scenarios with different fire location in the tunnel. Values correspond to mean and standard deviation.

tg_{I-II}^{early}	tg_{II-III}^{early}	tg_{III-IV}^{early}
-9.00 ± 12.40 s	-7.51 ± 7.26	-6.25 ± 6.13
tg_{I-II}^{late}	tg_{II-III}^{late}	tg_{III-IV}^{late}
12.10 ± 8.24 s	8.04 ± 7.05 s	6.92 ± 7.21 s
$\overline{tg}_{I-II}$	$\overline{tg}_{II-III}$	$\overline{tg}_{III-IV}$
0.66 ± 11.28 s	-1.02 ± 7.87 s	0.90 ± 6.83 s

mented on these 200 simulations. It is noteworthy that each simulation was stopped until the quasi-steady of the fire was reached, as performed in previous simulations.

45,308 samples were obtained from the 200 scenarios. The proportion of each fire class is shown in Figure 2.15. The input parameters of samples were fed into the data-driven model previously trained for fire classification. To evaluate the impact of the fire location on the model performance, the degree of accuracy of the ANN in terms of time was determined. As previously mentioned, the determination of the ANN accuracy in terms of time can provide a better estimation of the uncertainty of the data-driven model in fire class predictions. Table

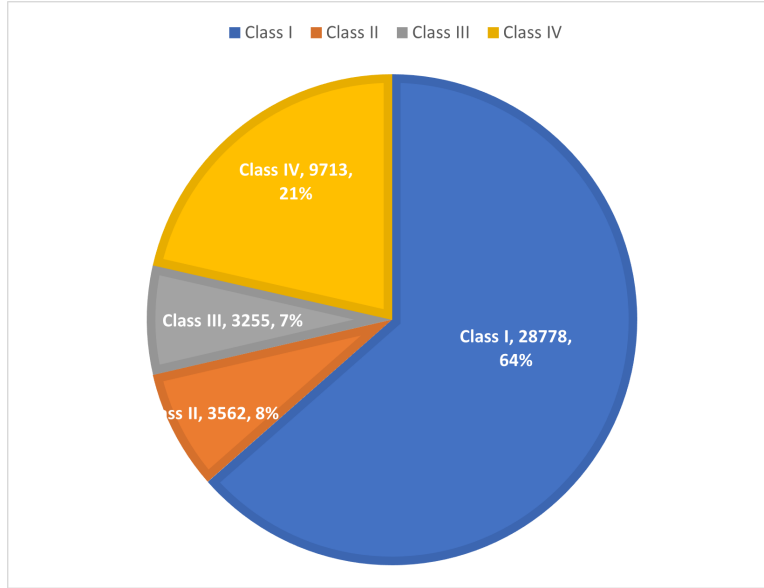


Figure 2.15: Number of samples and percentages per fire class for the 200 scenarios in which the fire location was varied.

2.17 shows the mean and standard deviation of tg_{x-y}^{early} , tg_{x-y}^{late} , and tg_{x-y} for the 200 scenarios. Based on these statistics, it can be stated that 95% of ANN predictions for fire class change should have a time gap within ± 18 s of the true fire class change when the fire location is varied. The impact on the data driven model accuracy was estimated to be around ± 9 s when compared to predictions in scenarios with a fixed fire position. This minimal impact can be explained due to a different evolution of upwind conditions for scenarios with taller fire positions. It is noteworthy that there is not an input parameter which can provide information to the ANN about the fire height. Thus, the predictive model is less precise since the evolution of upwind conditions can get worse faster for scenarios with taller fire position. Despite this, it can be said that the data-driven model capability is still very promising when the fire location is unknown. An uncertainty of 18 s during mine fire classification is very low knowing the reduced amount of input parameters available in underground coal mines.

2.4.2 Impact of fuel variation on data-driven model performance

For determining the impact of fuel variation on the data-driven model performance, the geometry of Scenario A was simulated using the fuel sources shown in Table 2.18. Methane properties were used to simulate a coal fire in Scenario B, which is a common event in underground coal mines [20]. Propylene was used to simulate a fire on a conveyor belt in Scenario C. Propylene is the most predominant gas after the pyrolysis of Styrene Butadiene Rubber (SBR) [37, 61]. SBR is a polymer widely used for the fabrication of conveyor belts in the mining industry since it provides excellent abrasion and heat resistance [43]. The heat of combustion as well as the soot and CO yields were adjusted to ensure that the proper amount of CO and soot were produced during the SBR pyrolysis and combustion reaction [96, 97, 111]. Heptane properties were [71] used to simulate a spill fire in Scenario D.

Figs. 2.16- 2.18 show the true and predicted fire class evolution in Scenarios B, C, and D. The data-driven model performed early and late predictions of all fire class changes during Scenario B and D, respectively. On average, the ANN predicted the true fire class change in Scenarios B 65 s early. In Scenario D the ANN predicted the true fire class change 50 s late on average. However, fire class predictions for Scenario C were more accurate, with an average of early fire class change prediction equal to 10 s. This variability on the ANN performance can be mainly explained because the CO release rate ($\dot{CO}$) calculated using Equation 2.8 is different for each fuel. During training, the ANN learns the relationship between the CO concentration and the attack position conditions for a specific fuel. Thus, if the fuel is varied, such a relationship learned by the ANN will be different, causing the model to perform significantly early or late predictions.

$$\dot{CO}(t) = \frac{Q(t)Y_{CO}}{\Delta H_c} \quad (2.8)$$

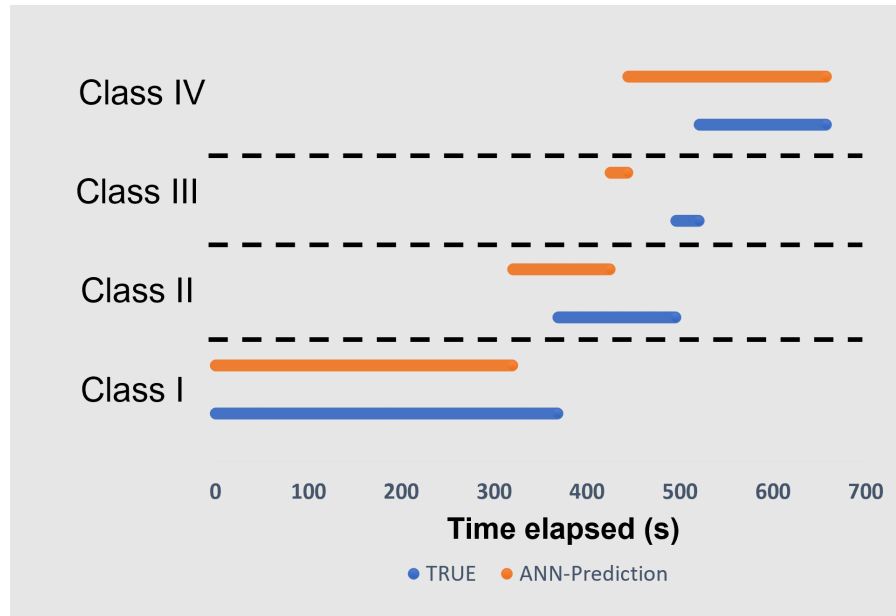


Figure 2.16: True and predicted fire class evolution in Scenario B. Blue and orange lines represent the true and predicted time elapsed on classes shown on the vertical axis, respectively.

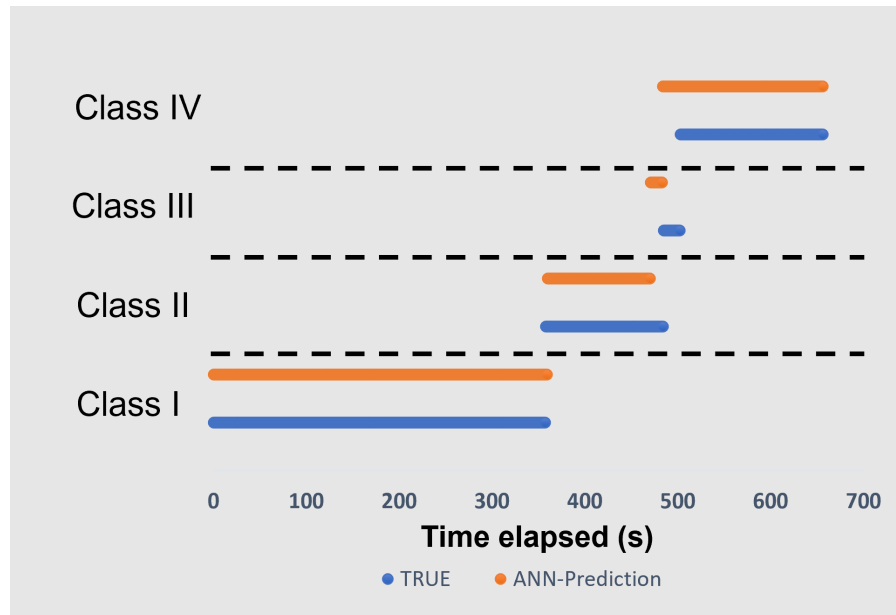


Figure 2.17: True and predicted fire class evolution in Scenario C. Blue and orange lines represent the true and predicted time elapsed on classes shown on the vertical axis, respectively.

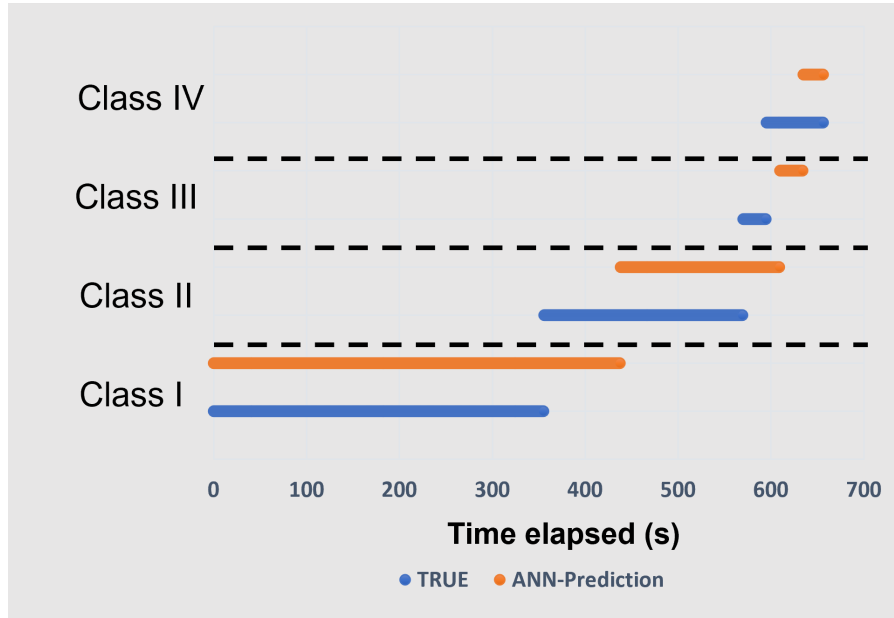


Figure 2.18: True and predicted fire class evolution in Scenario D. Blue and orange lines represent the true and predicted time elapsed on classes shown on the vertical axis, respectively.

Where, $\dot{CO}(t)$ is the CO release rate at any time(t), ΔH_c is the heat of combustion of the fuel, and Y_{CO} is the CO yield of the fuel.

The $\dot{CO}(t)$ of methane (Scenario B) is greater than the $\dot{CO}(t)$ of polyurethane which was the fuel used for training the ANN. This causes the ANN to make early fire class change predictions, since it interprets that conditions are worse at the attack position due to the high CO concentration downwind from the fire. While the $\dot{CO}(t)$ of the fuel is lower than the one used for training the ANN as in Scenario D, the ANN interprets that conditions are more favorable due to the low CO concentrations downwind from the fire. For this reason, the ANN predicts late fire class change in Scenario D. On the contrary, the ANN is much more precise in Scenario C since $\dot{CO}(t)$ of the propylene and polyurethane are similar. These results demonstrate that the data-driven model accuracy decreases if the fuel characteristics used for the ANN training differ from the characteristics of fuels involved in the fire. As mine fires can involve multiple fuels, which are generally known based on the mine location

Table 2.18: Alternative fuels to evaluate the fuel variation on the data-driven model performance. Heat of combustion, CO, soot, and CO_2 yields

Fuel	Chemical Formula	ΔH_c (kJ/kg)	Y_{CO}	Y_{SOOT}	Y_{CO_2}	Scenario
Methane	C_4H_4	55500	0.10	0.10	0.02	B
Propylene	C_3H_6	28500	0.12	0.11	0.01	C
Heptane	C_7H_{16}	44500	0.07	0.03	0.008	D

and the data-driven approach is site-specific, three approaches are recommended for the fuel selection during the elaboration of the data-driven approach to deal with the fuel uncertainty:

- Use the fuel with the highest $\dot{C}O$ that could be involved in the fire. This is the most conservative approach.
- Use a fuel with the average properties of the fuels that could be involved in the fire.
- Use the most predominant fuel at the location where the data-driven approach would be developed. For instance, if a data-driven model is developed to classify belt fires, propylene should be used.

2.5 Conclusion

A comprehensive data-driven approach was developed to classify fires with the objective of recommending the most suitable decision to the mine firefighting personnel. A feed-forward artificial neural network (ANN) was trained to classify fires using measurable and available data during ongoing underground coal mine fires as input parameters such as CO concentration, air velocity, time, and mine entry dimensions. The data for training and testing the network was generated from the analysis of FDS and FSSIM simulation

results of 500 fire scenarios of a flat and straight mine entry that simulates a belt entry. FDS simulations were used to determine the atmospheric conditions at the attack position allowing for the fire classification. FSSIM simulations were utilized to calculate the evolution of CO concentration downwind from the fire. Simulation results of both models were linked. This linking process generated 110,695 samples of which 80 percent were used for training and 20 percent for testing the robustness of the approach.

Results showed a network overall accuracy and weighted average F1-score of 97.0 percent for training and testing datasets. Much of the classification error can be attributed to the performance of the ANN classifying scenarios during the fire class change to Class II and III. This low performance for classifying Class II and III was understood to come from two primary sources. The first source is related to the evolution of the conditions at the attack position is not instantly exhibited in the variation of the CO concentration downwind from the fire. For air velocities lower than 1.6 m/s it was seen that the ANN tends to predict early the fire class change in scenarios with lower fire growth rates. Low fire growth rates mean longer scenarios times, causing the ANN predicts the fire class change early because of the long period of time elapsed. Conversely, the ANN tends to predict the fire class change late in scenarios with greater growth rates. The ANN assumes promptness for class change due to the short time elapsed. The analysis of results showed that 95 percent of ANN predictions for fire class change should have a time gap within ± 9 s of the true fire class change when the fire location is known.

Additionally, the impacts of fire location and the fuel variation on data-driven model performance were determined. 200 extra scenarios were simulated in which the fire location was varied. Results show that the impact of the fire variation on the model prediction performance is minimal. The time gap increased ± 9 s when the fire location varied. Overall, 95 percent of ANN predictions for fire class change should have a time gap within ± 18 s of the

true fire class change when the fire location is unknown. Regarding the fuel variation, it was determined that if the $\dot{C}O$ of the fuel(s) involved in the fire is different than the one of the fuel used for training, the prediction performance of the ANN is affected. The network learns the relationship between CO concentration and attack position conditions for the $\dot{C}O$ of fuel used during training. On the other hand, if the $\dot{C}O$ is similar to the one of the fuel used for training, the prediction accuracy of the ANN is not affected. Thus, three approaches were recommended to deal with the fuel uncertainty during the elaboration and utilization of the data-driven approach.

The performance metrics and statistics shown in this work highlight the capability of the data-driven approach to classify fires and inform decision making around firefighting with a high degree of precision in real time, despite the limited information available and measurable during mine coal fire events. The fact that the data-driven model can provide the most suitable decision in real time and has a high degree of accuracy makes this approach particularly promising for real time risk analysis during mine fire emergencies. This tool could increase the probability to extinguish fires without compromising the health and safety of firefighters. The methodology proposed could be implemented in different scenarios such as underground storage facilities and road tunnels and even using experimental data for more precise results. However, in case of higher complexity on fire scenarios where the methodology proposed can be extended (different geometries, fuels, fire locations, etc.), inputs to the predictive model must provide more information to capture the variability of scenarios. However, this will not be a problem in these types of scenarios since there could be more information available obtained by high-tech electrical devices such as heat, infrared, and video cameras. The use of more advanced devices could allow for the development of more complex data-driven approaches that use image processing techniques to determine atmospheric conditions and firefighting strategies with high degree of accuracy. Finally, additional de-

velopment is needed to incorporate additional physical components such as different types of fuel and reaction parameters that impact the atmospheric conditions during mine fires to provide broader and more realistic input to emergency situations.

Chapter 3

Fire size and response time predictions in underground coal mines using neural networks

3.1 Abstract

The prediction of the coal mine fire response time, defined as the remaining time before conditions at attack positions grow untenable for firefighters, plays a vital role in the decision-making process during a mine fire scenario. The knowledge of the response time along with the fire size, fire location and arrival time could allow for the most suitable decision regarding direct or remote approach to the fire in the mine, mine evacuation planning, and remote attack from the surface. For this reason, this paper presents a data-driven approach to predict the response time and fire size based on available and measurable parameters during underground coal mine fires using two interconnected artificial neural networks (ANNs). A total of 300 Fire Dynamic Simulator (FDS) and Fire and Smoke Simulator (FSSIM) simulations of a straight and flat mine entry (replicating a belt entry) with different fire sizes, air velocities and dimensions were used in training and testing the ANNs. The results showed that 95% of fire size and response time predictions should be within ± 29 kW and ± 4 s of true values obtained in the fire models, respectively. The approach presented in this

work can provide instantaneous predictions of response time and fire size during ongoing mine fires. Additionally, this approach can be utilized in other mine fire locations as well as in different types of tunnels.

3.2 Introduction

Once a fire is discovered in an underground coal mine, a decision-making aims to reduce the probability of high-risk event. Among these options are the possibility of attacking the fire directly or through remote techniques when conditions are not tenable for the firefighting personnel. In most underground mine fires, direct attack at the initial stages is usually a priority since fires develop rapidly. If a fire cannot be controlled by direct firefighting methods, the probability of effectively extinguishing the fire without the need to seal the mine or a portion of the mine is greatly reduced [8, 17, 18, 100]. However, considering the accessibility of coal mines and the potential remote locations of fires, some fires cannot be attacked during their first stages. Conditions at the fire proximity can grow untenable preventing firefighters' approach to carry out direct attack. Thus, predictions of the evolution of the conditions in the proximity of the fire could allow for the determination of the response time defined as the remaining time before conditions at attack positions become untenable for firefighters. The determination of the response time along with the knowledge of the fire size, fire location and arrival time allows for the most informed and methodical decision regarding the type of attack. These decisions must be made relatively quickly, so there is a need for a new approach that can determine the response time and fire size in real time during ongoing mine fire scenarios. This approach must use measurable and available parameters in underground coal mines in order that it can be applied in the field.

To predict the conditions generated by enclosed fires such as in underground mines, two

types of models have been used: computational fluid dynamics (CFD) fire models and zone fire models (ZFM) [8, 38, 47, 88, 91, 109]. In CFD fire models the Navier-stokes equations of mass, momentum, and energy are solved as well as the species conservation equation in discretized geometries allowing for the spatial-temporal resolution of the entire domain. Parameters such as concentrations of combustion gases, temperature, visibility, and radiation in each grid cell are solved. However, the high computational cost and processing time of these models that can be in order of days or even weeks makes it impractical to use in informing real-time conditions. On the other hand, in zone fire models the domain is divided into larger compartments which are represented as single nodes (Peacock, Forney, and Reneke 2015). This approach of having one node per control volume minimizes the computational cost and time allowing for faster predictions of smoke spread in larger domains. Although zone fire model simulations can be obtained much faster than CFD models, it is still unfeasible to solve entire domains and process results in real time. In addition, it is noteworthy that ZFM predictions have low spatial resolution for hazard analysis.

Advancements in machine learning and improvements in computing power have contributed to an increase in the usage of artificial neural networks (ANNs) for development of data-driven models able to solve domains and process results in real time [11, 42, 54, 55, 68, 75, 83]. ANNs can learn complex dependencies between variables which makes them an attractive technology for this kind of application. For instance, Hodges, Lattimer, and Luxbacher [42] recently used machine learning to approximate the detailed thermal flow field in a mine fire showing the capability of ANNs to predict conditions in underground mines. Nevertheless, this study did not focus on evaluation of atmosphere conditions nor calculation of response time and fire size. An approach which uses measurable and available parameters as inputs to a machine learning model to determine response time and fire size in real time is particularly promising for decision making during fire emergency response.

The objective of this study was to develop a data-driven model to make predictions of response times and fire sizes in real-time based on on-site CO concentration sensor readings downwind from the fire and other known operating parameters such as mine geometry, air velocity and time elapsed after fire detection. This approach was implemented for different fire scenarios in a straight and flat mine entry (replicating a belt entry) with different fire characteristics, air velocities and dimensions. The data used for training and testing the data-driven approach was generated using a CFD model called Fire Dynamics Simulator (FDS) and a zone fire model called Fire and Smoke Simulator (FSSIM). FDS was used for the determination of conditions in the proximity of the fire where the attack position is located. FSSIM was used to determine CO concentrations downwind from the fire. The entire model was composed of two interconnected feedforward ANNs in which the prediction of the fire size performed by the first ANN is used by the second ANN to predict the response time. The approach presented in this work can provide instantaneous predictions of fire size and response time during ongoing mine fires and be applied to other mine fire locations as well as in different types of tunnels.

3.3 Methodology

A sketch showing a high-level view of the solution algorithm used to develop the data-driven approach for prediction of fire size and response time is shown in Figure 3.1. ANN-1 makes predictions of fire size using input parameters measured in mines. Fire size predictions by ANN-1 along other operating parameters are used as input to ANN-2 for response time determination. Data for training and testing ANNs was generated using FDS and FSSIM simulations. A tenability analysis was performed for calculation of response time in different scenarios. The following subsections describe the network architecture, tenability analysis,

and data generation and preparation used in this work.

3.3.1 Network architectures

The entire model for the determination of fire size and response time used in this study is composed of two interconnected ANNs as shown in Figure 3.2. The main constraint for the elaboration of the predictive model was to use only available and measurable parameters during underground coal mine fires as inputs to the ANNs. According Title 30 CFR §75.351(e)(f)(h), underground coal mines are required to be monitored of carbon monoxide by atmospheric monitoring systems (AMS) or CO systems [101]. As defined in Title 30 CFR §75.301, AMS or CO systems are described as networks consisting of hardware and software capable of measuring atmospheric parameters and transferring the measurements to a designated surface location. For CO monitoring, sensors of these systems must be located at key locations such as belt and return entries, working faces, electrical installation locations, and primary escapeways. This indicates that during mine fires, CO concentration is measured at different mine locations and transmitted to surface in real time in all US underground coal mines. CO is a combustion product which its concentration contains information of the fire size and conditions during ongoing mine fire. Thus, CO concentration was selected as one of the input parameters to the predictive model. In addition to CO concentration, there are known operating parameters that can impact fire conditions. These known parameters are mine entry dimensions, time elapsed after fire detection, and nominal longitudinal air velocity. They are all known since they are part of the mine operating procedures. These additional parameters were used along with CO concentration as input parameters to the ANNs.

The architecture of the first ANN (ANN-1) consists of fully connected layers of which three

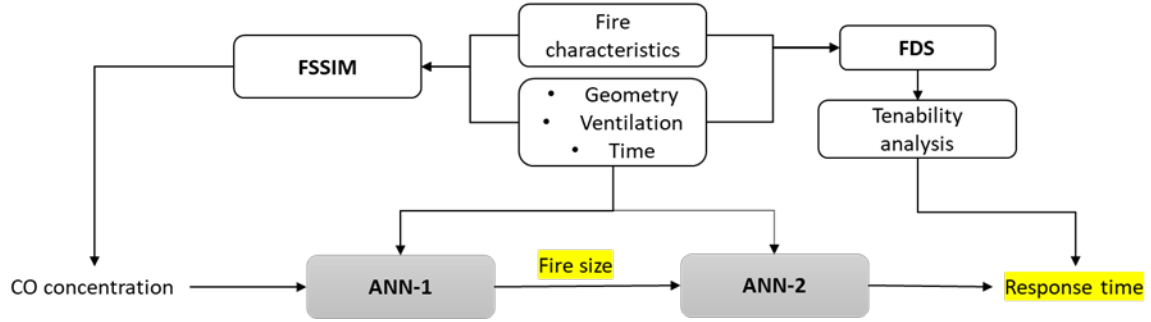


Figure 3.1: Sketch of solution algorithm

are hidden layers of 30 neurons as shown in Figure 3.2. The input layer is composed of 5 elements that as mentioned previously corresponds to longitudinal air velocity, tunnel width, tunnel height, CO concentration, and time elapsed after fire detection. The output layer consists of one element that refers to the fire size prediction which is included in the input vector of ANN-2. The architecture of ANN-2 also consists of three hidden layers of 36 neurons for a total of 5 fully connected layers as shown in Figure 3.3. The input vector of ANN-2 consists of 5 elements that corresponds to fire size, velocity, tunnel width, tunnel height, and time elapsed after fire detection. In both ANNs the rectified linear unit activation function (ReLU) was used for the hidden layers. The Adam gradient descent optimization algorithm with the mean squared error as loss function was used. 10,000 epochs with a batch size of 100 samples and a learning rate fixed at 10-2 were used for training both ANNs. All weights and biases were initialized from a normal distribution with zero mean and 10^{-2} standard deviation. The network architecture was created using Keras, a high-level neural network library built-in Python that runs on top of TensorFlow, an open-sourced end-to-end platform [1, 15].

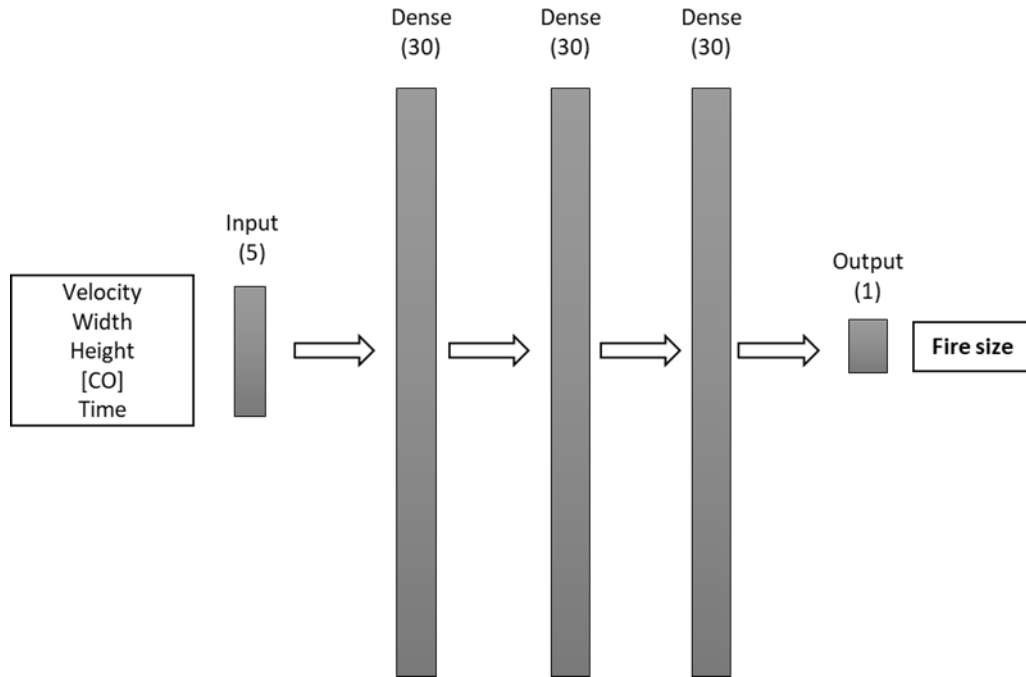


Figure 3.2: Architecture of ANN-1

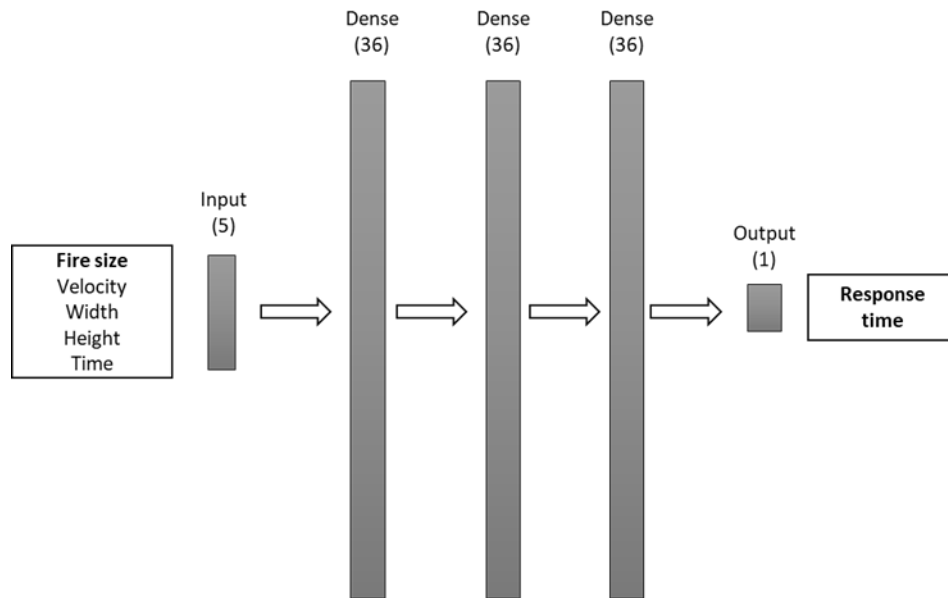


Figure 3.3: Architecture of ANN-2

3.4 Tenability analysis

The tenability analysis allows for the determination of the parameters and limits that should be considered to evaluate the tenability of the conditions in the fire proximity. US mining regulation requires that each operator of an underground coal mine drafts an emergency and firefighting program that guides all miners in the procedure that they must follow if a fire occurs [101]. The regulation stipulates that during a mine fire some miners are designated to respond to the mine fire emergency while other miners are required to evacuate the mine. Mining regulation specifies that at least two miners in each working section and one miner for every four miners on a maintenance shift must be proficient in the use of fire suppression equipment available in the mine and know its location [101]. The underground miners assigned to address the fire are called the first responder group (FRG) since they are the first group to deal with the fire. The FRG is commonly composed of barefaced personnel [18].

In addition to the FRG, there is a second group composed of specially trained fire brigade and mine rescue team called the second responder group (SRG). Although a fire brigade is more focused on firefighting, the mine rescue team may also conduct firefighting activities during rescue procedures. Mining regulation requires every operator of an underground mine shall establish at least two mine rescue teams which are available when miners are underground [101]. The SRG has more specialized personal protective equipment (PPE) such as turnout gear and self-contained breathing apparatus (SCBA). Moreover, this group normally carries firefighting equipment that includes efficient water hose nozzles with pistol grips allowing the members of this group to attack fires with more control of water patterns and flows [18].

The tenability analysis carried out in this study is based on previous tenability analysis performed in road tunnels [33, 45, 78] and in a simulated methane fire event at the working

face in a coal mine [39]. Following these analyses, four main parameters should be considered during tenability analysis. The parameters are toxicity, temperature, visibility, and radiation. In this study the data-driven approach was only developed to determine response time for the SRG, thus temperature, radiation, and visibility were only considered. It is noteworthy that for the SRG the toxicity is not accounted since this group normally carry SCBA designated to provide oxygen for at least 4 hours and are suitable for firefighting. In some tenability analyses previously performed some limits are determined for certain time of exposure such short-term exposure limits (STEL). However, in this study limits were established as ceiling or critical limit as also recommended by Gehandler et al. [33]. In real mine fires and numerical simulations have been observed that when parameters reach numbers close to the exposure limits, it is almost a certainty that they will keep increasing if the fire is not attacked. In addition, visibility is generally the first tenability parameter limit exceeded (well before limits for toxicity, temperature, and radiation) and its limit is always considered a critical limit due to the difficulty that firefighters have performing essential activities such as fire approaching, firefighting, and evacuation. Considering the accessibility of underground coal mines and the remote location of fires this assumption assures a conservative approach.

The temperature and radiant heat limits for the SRG are determined by Haghighat and Luxbacher [39], and NFPA [78], respectively. Haghighat's work proposed a temperature of 100 °C for SRG wearing turnout gear. NFPA says that for SRG a radiation level under roughly 5 kW/m² can be withstood for around 7 minutes. However, in this study this value was considered the ceiling limit. Regarding visibility, its tenability limit is commonly established based on its impact on firefighters walking speed. Studies have been performed to determine the walking speed in function of the visibility and the extinction coefficient [30]. For purposes of this work, the tenable visibility limit was set to 5 m based on Gehandler et al. [33]. They mentioned that this visibility limit can be set as long as firefighters know the

Table 3.1: SRG Tenable limits

Parameter	Ceiling limit
Methane (kW/m ²)	<5.0
Temperature (°C)	<100
Visibility (m)	>5

environment where the fire occurs. It is noteworthy that a maximum visibility of 30 m was set in FDS. An optical coefficient equal to 3 [69] was used assuming light reflecting signs hanging on walls that indicate evacuation route as it is common in underground coal mines. Explosibility was not considered in this study, however if fire firefighters observe or suspect an explosive atmosphere during an ongoing fire (e.g., methane concentration between 5-15% with an oxygen concentration between 15-20%), the response time must be zero and the scenario must be considered as not tenable immediately. A summary of the tenability limits used in this study are summarized in Table 3.1.

3.4.1 Data generation

As stated previously, the data used to train and test the data-driven approach was generated from numerical simulations. 300 fire scenarios in a flat and straight mine entry were simulated in FDS and FSSIM. FDS simulations provided spatial-temporal results to determine the conditions in the fire proximity. FSSIM simulation results were used to determine CO concentration at sensor stations within 300 m downwind from the fire. It is noteworthy that in all scenarios simulated at least one tenability limit was exceeded to determine the response time. Figure 3.4 shows the locations in which CFD and FSSIM simulations were performed with reference to the fire position.

CFD data generation

CFD simulations were carried out to determine the conditions at the attack position using FDS. FDS is a large-eddy simulation model that solves the equations of mass, momentum, energy, and species conservation equations to determine the conditions due to the evolution of fire, transport of gases, and smoke in an enclosed space [69]. These equations are solved using the method of finite differences on a collection of uniformly spaced-three-dimensional grids [69] allowing for the predictions of parameters such as combustion gas concentrations, visibility, heat flux, soot fraction in each grid of the domain.

The geometry used in FDS simulations is shown in Figure 3.5. It was assumed that the fire location in these scenarios was located at a belt entry between two crosscuts as shown in Figure 3.4. The simulation input parameters varied in this study are shown in Table 3.2 and highlighted in Figure 3.5. These parameters were selected since they have direct influence on the presence and amount of backlayering [58, 59, 81, 98, 99, 103, 108]. Backlayering is defined as the reversal flow of smoke and combustion gases within a tunnel (towards the forced ventilation) affects the visibility and toxicity at the attack position leading to untenable conditions. During direct attack firefighters approach the fire and position themselves approximately 5 m upwind of the fire. At this attack position they proceed to try and suppress the fire using water or firefighting foam. For this reason, FDS simulations were used to determine the conditions at the attack position assumed to be 5 meters away upwind of the fire and at a height of 1.5 m. A height of 1.5 was selected since firefighters would try to crouch when they attack the fire with the objective to stay below the smoke layer as was also assumed by Haghighat and Luxbacher [39].

The values of parameters shown in Table 3.2 for each scenario were obtained using simple random sampling from uniform distribution in which each value has the same probability

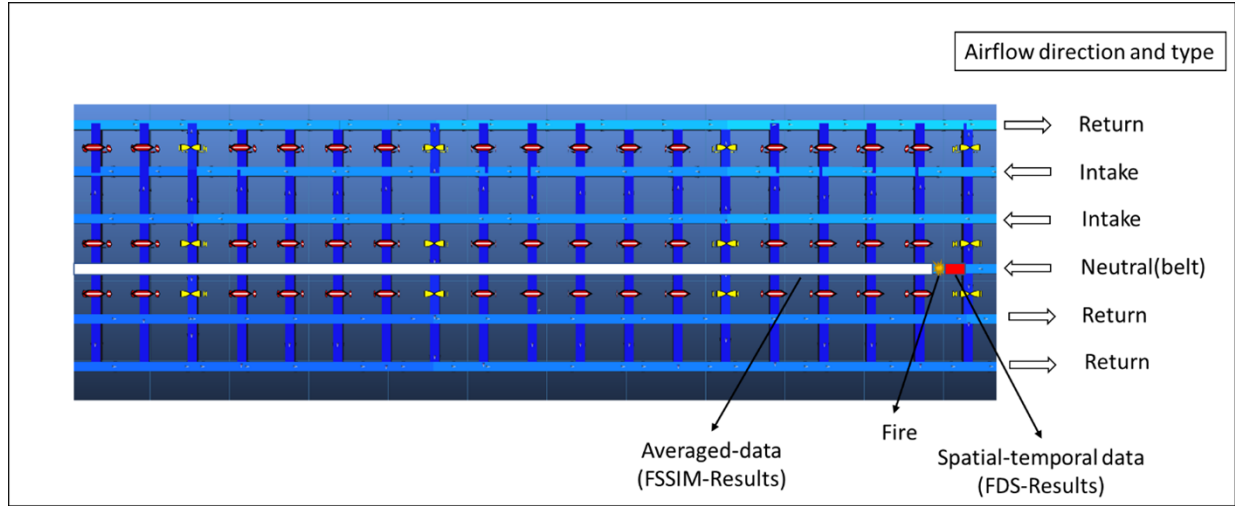


Figure 3.4: Locations of FDS and FSSIM results (plan view of mine ventilation schematic)

Table 3.2: Range of each parameter in study

Parameter	Range
Air velocity (m/s)	0.5-2.0
Fire size (kW)	750-7000
Fire growth rate (s^{-1})	0.01172-0.1876
Height(m)	1.8-2.8
Width(m)	5.0-7.0

of being drawn during the sampling process. However, it was assured that conditions grow untenable for firefighters in all scenarios to determine the response time. The simulation time of the 300 FDS scenarios varied depending on the fire size and growth rate. Each scenario was determined to last until the time the maximum fire size ($t_{\max}$) is reached. The fire size at time (t) was determined using the T-squared approach shown in Equation 1 for all scenarios.

$$HRR(t) = \alpha t^2 \quad (3.1)$$

In the above equation, HRR is the fire size at a time (t) and α is the fire growth rate that it is defined as shown in Equation 3.1. Note that the lower and upper limits of the fire growth rate range refer to the standard medium and ultrafast growth rates, respectively.

$$\alpha = \frac{HRR_{max}}{t_{max}^2} \quad (3.2)$$

Where, HRR_{max} is the maximum fire size reached at t_{max} .

The grid size (dx) was 0.1 m along each axis of the domain for all simulations to reduce calculation time and computational cost as well as have consistent results. McGrattan, Baum, and Rehm [73] recommend a grid size value less than or equal to $0.1D^*$ to completely resolved the source fire. D^* refers to the characteristic length scale that corresponds to the total HRR of a fire plume defined in Equation 3.3. Although the grid size used in this study does not fully resolve the source fire for sizes lower than 1,000 kW, the predictions were adequate for exploratory analysis to test the ability of ANNs to make predictions than comparing to experimental results. The range of D^*/dx is between 21 and 9 for fire sizes of 7000 kW and 500 kW, respectively.

$$D^* = \left(\frac{Q}{\rho C_P T_0 \sqrt{g}} \right)^{2/5} \quad (3.3)$$

Where, D^* is defined as the characteristic length, Q is the heat release rate of the fire, ρ is the air density, C_P is the air specific heat, T_0 is the ambient temperature, and g is the gravity acceleration.

The parameters shown in Table 3.1 were determined during the simulations since they allow for the evaluation of conditions for firefighters as detailed in Section 3.4. The value of each parameter was calculated at intervals of 1 second at the attack position. Flexible polyurethane

Table 3.3: Heat of combustion, CO, soot, and CO₂ yields of the material involved in the fire

Material	Heat of Combustion (kJ/kg)	Y _{CO}	Y _{SOOT}	Y _{CO₂}
Polyurethane	25300	0.02775	0.1875	1.5325

foam was used as the material to simulate the fire in each scenario. Characteristic of flexible polyurethane foam are shown in Table 3.

Zone fire model data generation

To determine the CO concentration downwind of the fire, FSSIM was used. In FSSIM each control volume or compartment is represented as single node. Junctions that represent flow paths are defined between nodes. The approach of just having one node per control volume minimizes the computational cost and time allowing for predictions of smoke spread in larger domains such as large areas in underground coal mines. FSSIM solves the 1-D conservation equations for mass, momentum and energy [28]. In zone fire models it is assumed that properties such as temperature, density and chemical species take constant values through each zone.

The 300 scenarios simulated in FDS were also simulated in FSSIM using the same input parameters and fuel characteristics shown in Table 3.2 and Table 3.3, respectively. FSSIM simulations were used to determine the CO concentrations within 300 m downwind from the fire in each scenario. The downwind CO concentration was determined at intervals of 1 second at 4 different sensor stations with a spacing of 75 m as shown in Figure 3.6. The geometry used in FSSIM consisted of a flat and straight mine entry 400 m long and split into 80 compartments. Thus, the length of the compartments was 5 m. The tunnel height and width depended on the mine entry dimensions of each scenario. The fire was located 17.5 m away from the inlet. The maximum CO concentration detected at the sensor stations at

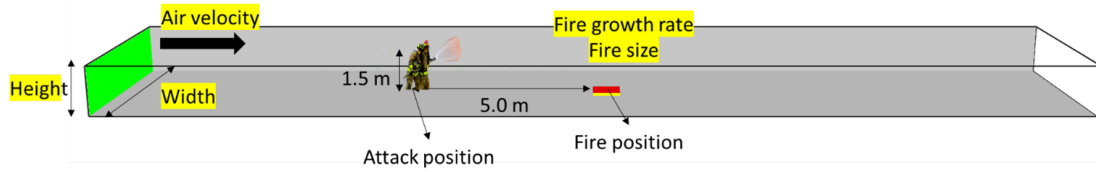


Figure 3.5: FDS geometry. Parameters varied in simulations are highlighted

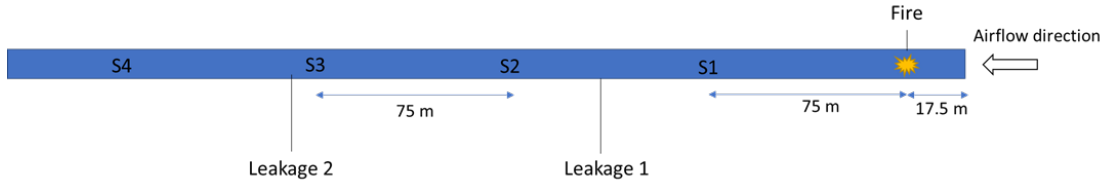


Figure 3.6: Geometry used in FSSIM, location of sensor stations, fire, and leakages

each time step was used as input parameter in the data-driven approach. Two air leakages along the tunnel were considered based on the location of crosscuts downwind from the fire as shown in Figure 3.6. The airflow quantities at leakages points were calculated based on mine survey results from a partner mine.

Data preparation

During the data preparation simulation input parameters and numerical results of FDS and FSSIM were processed with the objective of being used for training and testing the ANNs and the entire model (interconnected ANNs). The first step consisted of linking input parameters with FDS and FSSIM results. This can be done because same scenarios were simulated in both models. With the objective to be more illustrative with the linking process, the linking of three samples of Scenario A shown in Table 3.4 is detailed in what follows. Based on time elapsed and fire size it was possible to link tenability parameter results at the attack position predicted by FDS with the CO concentration downwind from the fire predicted by FSSIM. This is possible since time elapsed and fire size are equally predicted at any time in

Table 3.4: Simulations input parameters and simulation results of both fire models linked for three different time steps of Scenario A

Scen.	Simulation input parameters				FDS/FSSIM		FDS		FSSIM
	Vel (m/s)	Max fire size (kW)	Growth rate (s-1)	Dim (H x W) (m x m)	Fire size (kW)	Time (s)	Temp (C)	Vis. (m)	[CO] (ppm)
A	1.4	5182	0.012	2.8 x 6.2	450	194	20	30	5
A	1.4	5182	0.012	2.8 x 6.2	747	250	21	30	10
A	1.4	5182	0.012	2.8 X 6.2	2594	465	43	6	42

both fire models as shown under FDS/FSSIM column in Table 3.4.

Once parameters from both models were linked, the maximum response time for each scenario was calculated. This was carried out looking for the time in which at least one of tenability limit was exceeded in each scenario. For instance, in scenario A the maximum response time was determined at 466 seconds when the tenability limit of visibility was exceeded. It is called maximum response time because it is referenced from the fire detection ($t = 0$ s). Then, to determine the response time for each time step associated with the CO concentration and the other input parameters (tunnel dimensions, air velocity and time elapsed), the value of maximum response time was subtracted by the value of each time step. After calculation of response time for each time step, the inputs and outputs of the models were assigned. In Table 3.5, Table 3.6, and Table 3.7 are shown the values of the input and output parameters for the first and second ANNs, and the entire model (interconnected ANNs) based on results of Scenario A shown in Table 3.4, respectively.

3.5 Results and discussion

After processing 300 simulation results from FDS and FSSIM, 24,694 samples were collected for training and testing ANNs and testing the entire model. The entire dataset was randomly

Table 3.5: Values of input and output parameters of the ANN-1 for three samples of Scenario A

Scenario	Inputs					Output
	Time (s)	[CO] (ppm)	Vel (m/s)	Height (m)	Width (m)	Fire size (kW)
A	194	5	1.4	2.8	6.2	450
A	250	10	1.4	2.8	6.2	747
A	465	42	1.4	2.8	6.2	2594

Table 3.6: Values of input and output parameters of the ANN-2 for the three samples of Scenario A

Scenario	Inputs					Output
	Time (s)	Fire size (kW)	Vel (m/s)	Height (m)	Width (m)	Response time (s)
A	194	450	1.4	2.8	6.2	272
A	250	747	1.4	2.8	6.2	216
A	465	2594	1.4	2.8	6.2	1

Table 3.7: Values of input and output parameters of the ANN-2 for the three samples of Scenario A

Scenario	Inputs					Output
	Time (s)	[CO] (ppm)	Vel (m/s)	Height (m)	Width (m)	Response time (s)
A	194	5	1.4	2.8	6.2	272
A	250	10	1.4	2.8	6.2	216
A	465	42	1.4	2.8	6.2	1

split into two, with 80 percent for training and 20 percent for testing. The ANNs were trained independently using the training data. The performance of ANN-1, ANN-2, and the entire model on each dataset was determined. ANN-1 was tested based on fire size predictions. ANN-2 and the entire model were tested based on response time predictions. During the performance evaluation of the entire model, inputs of ANN-1 were feed to the entire model and error for response time predictions was determined.

In order to determine the performance of ANN-1, the error for fire size predictions was calculated as follows:

$$E_{FS,ANN1} = FS_T - FS_{ANN-1} \quad (3.4)$$

Where $E_{FS,ANN1}$ is the error for fire size, FS_T is the true fire size, and FS_{ANN-1} is the fire size predicted by ANN-1.

In the same way, for the determination of the performance of ANN-2 and the entire model, the error for response time was calculated as follows:

$$E_{RT,ANN2} = RT_T - RT_{ANN-2} \quad (3.5)$$

$$E_{RT,MODEL} = RT_T - RT_{MODEL} \quad (3.6)$$

Where, $E_{RT,ANN2}$ is the error for response time when ANN-2 is evaluated, RT_T is the true response time, RT_{ANN-2} is the response time predicted by ANN-2, $E_{RT,MODEL}$ is the error for response time when the entire model is evaluated, and RT_{MODEL} is the response time predicted by the entire model.

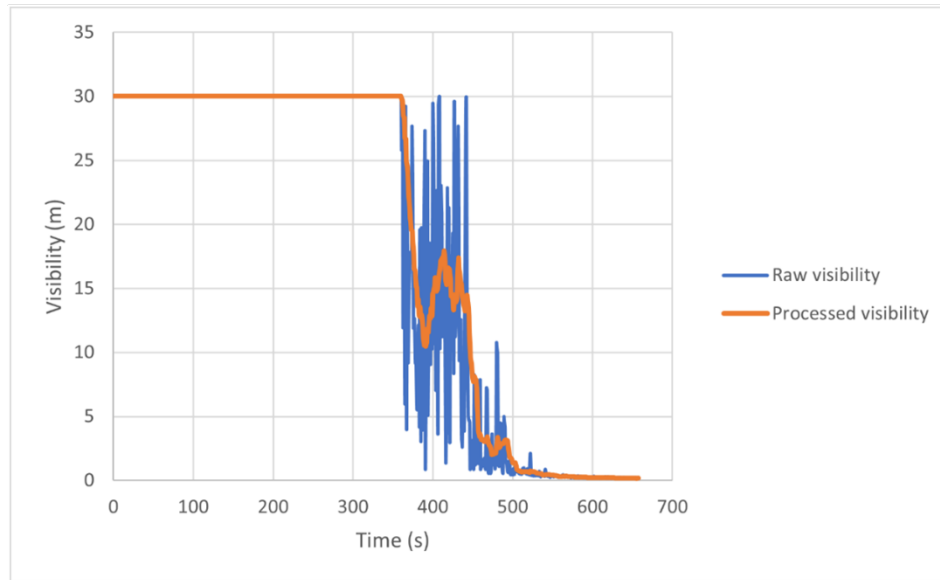


Figure 3.7: Raw and visibility over time for Scenario A

Due to the fluctuations inherent to the turbulent flow in FDS simulation, FDS results were processed applying an average filter with a window of 15 seconds in order to reduce the noise of the data. Figure 3.7 shows the evolution of visibility over time for Scenario A before and after applying the average filter.

The discrete probability density function of fire size error (ANN-1) and response time error (ANN-2) for all training and test data when ANNs were evaluated independently are shown in Figure 3.8 and Figure 3.9, respectively. Figure 3.10 shows the discrete probability function of response time error when the entire model was used for all training and test data. The mean and standard deviation of error predictions of ANN-1, ANN-2, and the entire model are summarized in Table 8. An error of zero indicates perfect agreement between the ANNs predictions and true values obtained from fire models.

Table 8 shows the mean fire size error of ANN-1 is -1.61 kW with a standard deviation of 12.97 kW for training set and a mean fire size error of -1.69 kW with a standard deviation of 14.36 kW for the test set. Based on this result it can be stated that 95% of ANN-1

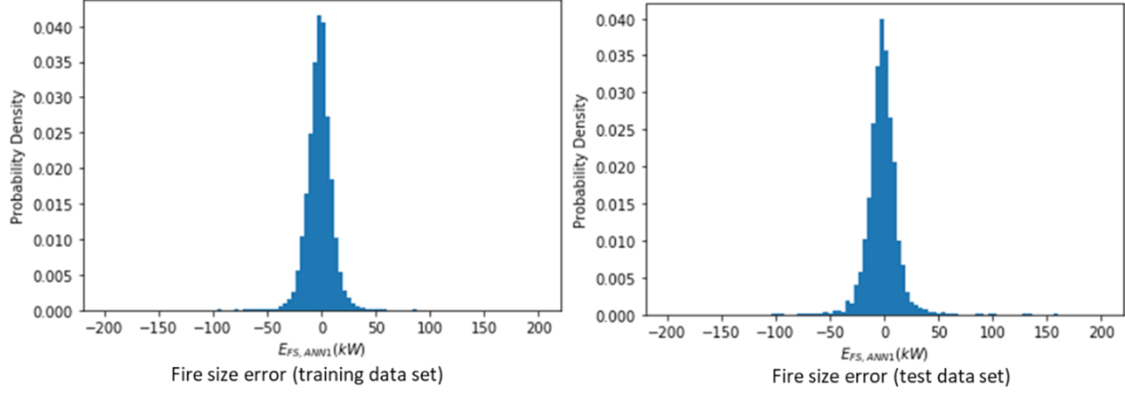


Figure 3.8: Discrete probability density functions of ANN-1 error from training and testing data set

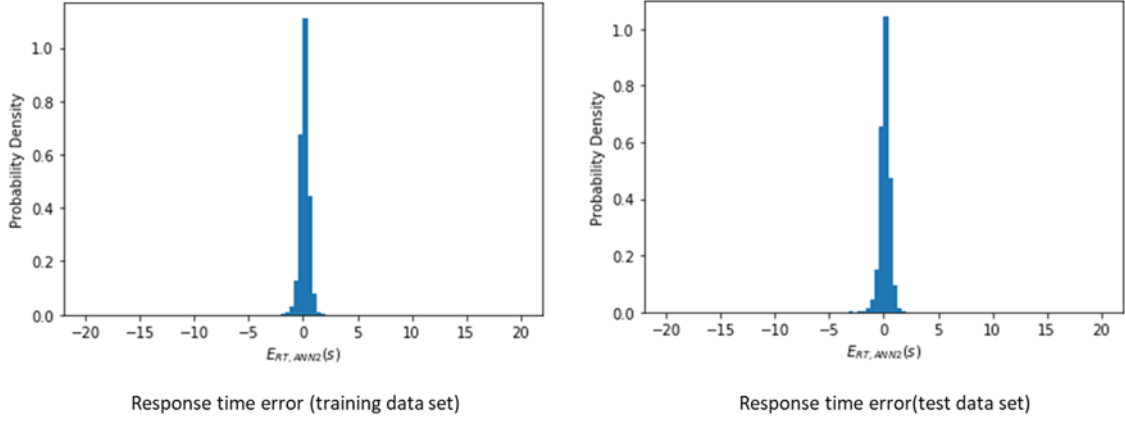


Figure 3.9: Discrete probability density functions of ANN-2 error from training and testing data set

Table 3.8: Summary of performance of ANN-1, ANN-2, and entire model on training and test data (values refers to $\mu \pm 2$)

Model	Prediction	Training Set Error	Test Set Error	Unit
ANN-1	Fire Size	-1.61 ± 12.97	-1.69 ± 14.36	kW
ANN-2	Response Time	0.13 ± 0.40	0.13 ± 0.43	s
Entire Model	Response Time	-0.36 ± 1.80	-0.33 ± 1.84	s

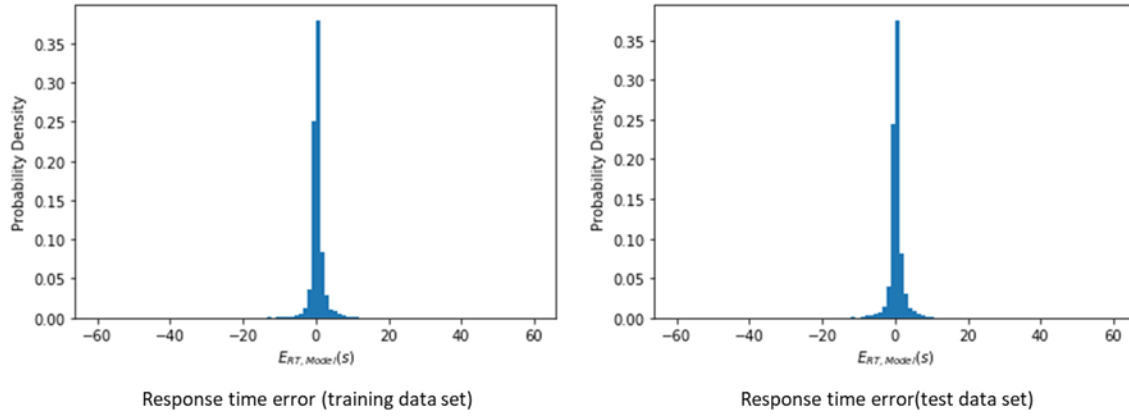


Figure 3.10: Discrete probability density functions of the entire model error from training and testing data set

predictions should be within ± 29 kW which highlight the capability of ANN-1 to predict the current fire size only using available information during ongoing mine fires. However, much of the fire size error in ANN-1 predictions was identified to come from two sources. The first source was related with the evolution of the fire size is not immediately reflected in the variation of the CO concentration measured by the sensors downwind from the fire. The longitudinal air velocity of each scenario has a significant influence on the CO concentration travel time from the source to the sensor locations. There is a velocity range in which ANN-1 performs well: however, for lower or higher velocities in this range, ANN-1 become less accurate. In addition to air velocity, different flowrates produce more diluted or higher CO concentration downwind from the fire. These two parameters cause a wide variability in the data that cannot be completely captured by ANN-1 with the input parameters used. In order to determine the relationship between ANN-1 performance and air velocity, the mean fire size error and standard deviation for scenarios with different air velocities were determined as shown in Table 3.9. Table 3.9 shows that the best performance of ANN-1 is when fire size is predicted for samples of scenarios with velocity between 1.0 and 1.5 m/s. The lowest mean fire size error and standard deviation were evidenced in this range. On

Table 3.9: Summary of performance of ANN-1 and number of samples for different velocity ranges

Velocity Range (m/s)	Error ($\mu \pm 2$)	Number of samples
0.5-1.0	-2.18 ± 19.75	4818
1.0-1.5	-0.63 ± 10.43	14043
1.5-2.0	-3.6 ± 12.38	5833

the other hand, greater mean fire size errors and standard deviations were seen for scenarios with air velocity in the range of 0.5-1.0 m/s and 1.5-2.0 m/s.

The second error source is related to the number of samples in each velocity range. Table 3.9 shows that higher errors were obtained for velocity ranges with lower number of samples. The low number of samples in the velocity range of 0.5 and 1.0 m/s is explained due to the short time in which the conditions are tenable at the attack position. The response time for scenarios with lower air velocities generally is short, thus the number of samples generated in those scenarios is smaller. Regarding the number of samples generated in scenarios in the velocity range of 1.5 and 2.0 m/s can be stated that the small number of samples is explained due to the lower number of scenarios with these velocities in which the tenability limits are exceeded. Scenarios with greater air velocities requires larger fire sizes to grow untenable conditions for firefighters.

Two approaches may be considered to reduce ANN-1 error. The first approach is including more training data that increases the number of samples for the previously mentioned velocity ranges. The second approach is adding other input parameters that provide more information related to the fire evolution such as the maximum fire size or fire growth rate, but these parameters are not available or measurable during mine fires. Based on results shown in Table 3.8, the desired performance of ANN-1 is met considering the limitations in the availability of parameters during the mine fire emergency.

Regarding ANN-2, Table 3.8 shows that the mean response time error of ANN-2 is -0.13 s with a standard deviation of 0.40 s for the training set and a mean response time error of 0.13 s and standard deviation of 0.43 s for testing set. Based on these values, it can be stated that the that 95% of ANN-2 predictions should be within ± 1.0 s when the true fire size is used as input parameter. These results highlight the capability of ANN -2 to predict response times with high degree of accuracy when the true or actual fire size is used. The use of the actual fire size along with the other input parameters provide enough information to ANN-2 to capture data variability for having response time predictions with low error values.

The mean response time error of the entire model is -0.36 s with a standard deviation of 1.80 s for the training set. The mean response time error of the entire model is -0.33 s with a standard deviation of 1.84 s for the testing set. As mentioned previously, the input parameters from datasets were feed to ANN-1 and error was determined from response time predictions by ANN-2. This indicates that the fire size error of ANN-1 propagates to ANN-2 and explains why the entire model error is greater than ANN-2 error for response time predictions. Even though errors of fire size predictions by ANN-1 affects the performance of the entire model, 95% of the entire model predictions of response time should be within ± 4.0 s when available input parameters during underground coal mine fires are used.

3.6 Conclusion

A data-driven approach was presented to predict fire size and response time in real time for firefighters based on available and measurable input parameters during ongoing mine fires using two interconnected feedforward ANNs. The data for training and testing the ANNs were generated from 300 scenarios with different longitudinal air velocities, mine en-

try dimensions, and fire characteristic simulated in FDS and FSSIM. Simulations in the FDS model allowed for the determination of the conditions at the attack position assigned to be 5.0 m upwind from the fire. Simulations in FSSIM allowed for establishing the CO concentration evolution within 300 m downwind from the fire. After linking input parameters and simulation results from both models, 24,694 samples were collected of which 80% was used for training and 20% was used for testing the robustness of the approach. Results showed that 95% of fire size predictions were within ± 29 kW of the true fire size, and 95% of response time predictions were within ± 4.0 s of the true response time when testing data was used. The major fire size error was identified to come from predictions for samples with air velocities within 0.5-1.0 m/s and 1.5-2.0 m/s ranges. The variability in data caused by different air velocities and flowrates it is not entirely provided by input parameters of ANN-1. In addition, the small number of samples for these velocity ranges could be another cause of the fire size error. The largest response time error can be attributed to inaccuracies in the fire size predictions since when ANN-2 was tested using true fire sizes, the response time error was much lower. Thus, it can be stated that the fire size error of ANN-1 propagates to ANN-2 as fire size predicted by ANN-1 is used as input in ANN-2. This work demonstrates using available and measurable input parameters during ongoing mine fires in the data-driven approach is possible to determine the fire size and response time in real time. While the model presented in this work was designed for a belt entry, the same methodology could be implemented in other mine locations. It is noteworthy that the the data-driven approach is site-specific, which means that it can be used only in similar geometries of fire scenarios utilized for training. Additionally, this approach could be applied in different enclosed locations such as underground storage facilities and road tunnels where parameters collection can be performed from high-tech electrical devices such as heat-cameras not allowed in underground coal mines. Thus, more complex data-driven approaches that use image processing techniques could be developed. Finally, future work

is needed to incorporate additional physics components such as different fuels and reaction parameters that has direct influence on the conditions during mine fires to provide broader and more realistic input to emergency situations.

Chapter 4

Mine conveyor belt fire classification

4.1 Abstract

This paper presents a conveyor belt fire classification model that allows for the determination of the most effective firefighting strategy. In addition, the effect of belt design parameters on the fire classification was determined. A methodology that involves the use of numerical simulations and artificial neural networks (ANNs) was implemented. An approach previously proposed for modeling fires over conveyor belts was used. With the objective of obtaining some required modeling input parameter and verifying the capacity of this approach to get realistic results, CFD model calibration and validation were carried out using experimental test results available in the literature. Results indicated that scenarios with belt positions closer to the mine roof and greater tunnel heights require a higher longitudinal air velocity to be attacked directly. Furthermore, the belt fire classification model provided by the ANN had an accuracy around 95% when test scenarios were classified.

4.2 Introduction

After a fire is confirmed in a mine, personnel must be safely evacuated and the mine system brought back into balance by either containing or extinguishing the fire [17, 18]. During mine fire response two main decisions can be made: direct attack and indirect attack. Direct attack

refers to a firefighting process involving the application of extinguishing agents directly onto the burning fuel [79]. Indirect attack refers to a fire suppression at a considerable distance away from the fire where it is not possible to apply agents onto the burning fuel since evacuation of the fire area or mine is required [79]. Indirect attack in underground coal mines generally involves sealing which refers to enclose the fire area or entire mine in order to exclude oxygen or flooding with water or gases such carbon dioxide and nitrogen [29]. It is noteworthy that the type of attack must be selected based on the fire characteristics and conditions at the fire proximity. Mine fires such as conveyor belt fires can grow rapidly and deteriorate the conditions very fast [62, 82] in which a wrong decision will put at risk the mine personnel and could cause catastrophic consequences. Fire effects analysis prior to belt fire occurrence can provide insightful information allowing for the best decision that increases the probability to extinguish the fire without compromising the health and safety of the firefighting personnel.

If a belt fire cannot be extinguished within a short time after discovery using direct attack, the chance of safely controlling and extinguishing the fire quickly without evacuation and sealing is greatly reduced [18]. The selection of direct attack seems to be the best decision regarding time, cost, and mine productivity; however, direct extinguishing must be selected and carried out as long as the health and safety of the firefighting personnel are not compromised [48]. Title 30 CFR § 75.1502 (a) requires that each underground coal mine operator adopts and follows a firefighting program which instructs all miners in the proper procedures to follow in case of a mine emergency [101]. Nevertheless, these procedures leave some space for subjective decisions that could lead to risky situations due to the extreme conditions produced by the fire.

In order to analyze fire effects prior to their occurrence, CFD modeling has been used to reduce the number of large-scale experiments. Once CFD models are calibrated or validated,

they can provide useful information related to flame spread rate, fire size, amount of smoke, and toxic gases produced [70]. Yuan et al.[113] carried out a CFD model calibration and validation of a fire spreading over a conveyor belt in a mine entry based on results of a large-scale experimental test. The CFD model was in good agreement with experimental results in some fire characteristics such as flame spread rate, the maximum fire heat release rate (HRR), downstream maximum smoke temperature, and maximum CO concentration at the exit. This study evidenced that Fire Dynamic Simulator (FDS) software can be used as a tool to predict the effects of fires spreading over a conveyor belt in a mine entry under different physical conditions. In the same way, Edwards and Hwang [24] used FDS to model fire spread along ribs, roof, timber sets and over a conveyor belt in a coal mine entry. Results obtained from the CFD model overestimated the flame spread rate over the conveyor belt when they were compared with experimental data. This fact can be attributed to the lack of CFD model calibration with experimental data [113]. Similarly, Lowndes et al. [63] built a computational model in the three dimensional CFD software Fluent to characterize the initiation and spread of fire along surfaces of a conveyor belt mounted within a ventilated full-scale experimental test gallery. Numerical results showed a good capacity to qualitatively replicate the flame spread observed on the belt surfaces within the test gallery.

Even though CFD modeling techniques have expanded successfully in the recent years reducing the number of experimental tests, these tests will always be important for validation and calibration purposes. Multiple large-scale experiments studying fire spreading over conveyor belts have been carried out and reported in the literature. Lazzara and Perzak[53] conducted a test in a large-scale fire gallery in order to measure the flame front velocity as function of the imposed convective air velocity for a type of Styrene-Butadiene rubber (SBR). Results showed that the measured flame front velocity peaked at an air velocity equal to 1.5 m/s. Using the same fire gallery, Litton and others[62] presented two nomographs defining sensor

alarm levels and sensor spacing as a function of belt entry air velocity and belt entry cross sectional area. Subsequently, Perera and Litton[82] used the nomographs to understand and quantify the effects of air velocity on the detection of fires in underground conveyor belt haulageways. Another large-scale experimental test with the objective of determining the flame spread rate on a SBR belt was carried out by Rowland and Smith[86]. They tested different air velocities from 1.0 m/s to 4.0 m/s determining the highest spread rate of 7.41 cm/s for an air velocity of 2.0 m/s.

Haghighat and Luxbacher[39] carried out a tenability analysis for mine firefighters in underground coal fire scenarios. The authors examined the impact of a simulated methane fire at a continuous miner working face on conditions such as temperature, visibility, radiation, and toxicity. Several permutations of numerical simulations studying the impact of damage on ventilation controls were used to examine the risk to fire responders. The authors recommended tenable limits for different responders based on their equipment (i.e. barefaced miners, mine rescue team, and the fire brigade). This previous research showed the numerical models were able to provide valuable insights into the tenability within a mine fire. However, this study focused on a miner face fire rather than a conveyor belt fire. In addition, prior studies have been limited to a limited set of simulations, with no attempts made to provide general support for real-time decision making for emergency responders.

On the other hand, artificial neural network (ANN) is a machine learning technique widely used for classification problems in recent years. ANNs have been used in wildfire classification for fire detection, risk assessment and recognition of high potential area for fire occurrence due to its ability to solve no-parametric, non-linear, large scale and very complicated models [35]. Researchers have recently used machine learning to approximate the detailed thermal flow field encountered in a mine fire [42]. This study showed the strength of artificial neural networks to predict the conditions in a mine. However, this study did not focus on any

specific mine fire scenario (i.e. miner face or conveyor belt). In addition, the researchers did not provide general support for real-time decision making for emergency responders. A new machine learning based model which is able to provide decision making support for emergency responders would greatly improve fire risk analysis in a mine fire.

The objective of this study was to develop a conveyor belt fire classification model that allows for the determination of the most effective firefighting strategy, as well as the influence of belt design parameters on the fire classification. Parameters such as belt position, tunnel height, and width were studied and considered for the elaboration of the classification model. In order to achieve these objectives, a methodology that involves numerical simulation and a machine learning tool such as ANN was used. CFD simulations were used to study the effects produced by fires spreading over conveyor belts following the approach proposed by Yuan et al.[113]. CFD model calibration was carried out using experimental test results available to obtain some required input parameters and verify the capacity of this approach to get realistic results. Different ANNs were used for the determination of parameter effects and the belt fire classification model. Finally, it is worth saying that the methodology used in this study can be applied for classification of other mine fire types, such as working face fires and intake entry fires as well as the determination of models for critical velocity and response time in belt fire scenarios.

4.3 Conveyor belt fire stages and detection times

Fires occurring in conveyor belt entries generally progress in three different stages as shown in Figure 4.1. The first stage is related to a low temperature smoldering combustion of coal. Loose coal is deposited along the belt drive area such as conveyor idlers or electrical cables where due either frictional overheating or an electrical fault, coal is heated triggering

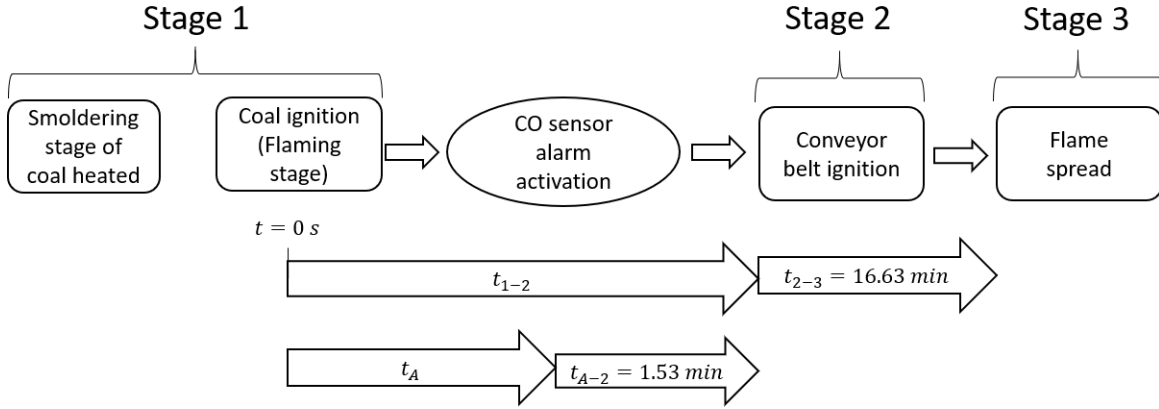


Figure 4.1: Conveyor belt fire stages in underground coal mines. Average times of CO alarm activation before the belt ignition and between stage 2 and 3 were determined based on results reported by Perera and Litton [82] and Litton et al.[62], respectively.

a smoldering combustion. Once coal temperature goes up, coal ignites, and flames appear. The second stage starts when the conveyor belt is stopped, and the heat produced by the coal fire is enough to ignite the conveyor belt. Finally, in the third stage the combined effect of coal and conveyor belt fires elevates the total fire intensity to the point of sustained belt flame spread [62, 82]. It is important to point out that the fire detection should occur as soon as possible in order to secure the safety of underground workers and firefighting personnel as well as to increase the probability of successfully controlling and extinguishing the fire. Title 30 CFR § 75.350 requires mine operators to monitor for carbon monoxide thorough CO sensors. Such CO sensors must be installed at intervals not exceeding 300 m along each belt entry [101].

In order to have a certain degree of understanding of the total time that firefighters have to approach the belt fire once it is detected, results of two previous experimental studies were used. These studies focused on belt fire detection time and time elapsed between fire stages. The first study was performed by Perera and Litton [82] that consisted of a large-scale experiment in which a conveyor belt composed of SBR material was used. In this study, the time elapsed between stages 1 and 2 (t_{1-2}), roof CO alarm activation time (t_A),

Table 4.1: Results of belt ignition times and CO detection times for a SBR conveyor belt reported by Perera and Litton[82].

Air Velocity (m/s)	t_{1-2} (min)	t_A (min)	t_{A-2} (min)
1.0	3.8	1.7	-2.1
2.0	15	16	1.0
4.1	7.8	4.3	-3.5

and the subtraction of these two times (t_{A-2}) for three different air velocities were reported as shown in Table 4.1. Times were referenced from Stage 1 when coal ignites ($t=0$ s). Thus, negative time values in column 4 represent that the fire detection was achieved before belt ignition. On average, results show that CO alarms are activated 1.53 min before the belt ignition. During the experimental test, sensors were spaced 300 m as required by the mining regulation, and fire was assumed to be 150 m away from each sensor. In the second study carried out by Litton et al.[62], the time elapsed between stages 2 and 3 (t_{2-3}) reported for different air velocities as shown in Table 4.2. The average time elapsed between stages 2 and 3 was estimated to be 16.63 min.

The extension of conveyor belts along underground coal mine entries are regularly in the order of tens of kilometers. For this reason, when belt fires occur in remote locations where there are no personnel around, firefighter deployment times are regularly greater than the time elapsed until the onset of the flame spread (around 18.16 min on average). Following a conservative approach and knowing that conditions can become untenable rapidly during belt fires, in this study it was strongly recommended remote attack in scenarios that result inadequate for direct firefighting after the onset of the flame spread. This turns out that if conditions remain tenable for firefighters after flame spread, direct attack must be carried out.

Table 4.2: Times elapsed between Stage 2 and 3 reported by Litton et al.[62].

Air Velocity (m/s)	$t_{2-3}(\text{min})$
0.76	15.5
1.52	18.5
1.52	17.0
4.06	15.5

4.4 Modeling the SBR

The modeling of flame spread over a conveyor belt is not an easy task since involves a complex interaction of highly non-linear phenomena. Flame spread over a conveyor belt is a process that involves gas phase turbulent flow, heat transfer between the flame, belt surface and surroundings surfaces, the vaporization of the belt material through the solid phase (pyrolysis reaction), and the chemical reaction of the gaseous fuel with the oxygen in the air. In addition, not all parameters related to materials involved in the pyrolysis process required for modelling are known [24, 70, 113]. Despite the complexity and limitations in flame spread modelling, Yuan et al. [113] proposed a simplistic approach for modeling flame spread over a conveyor belt using CFD technique. This approach overlooks underlying physics and the complexity of the fire spread phenomenon that could lead to not resolving the flame completely; however, numerical results of parameters needed in mine fire planning obtained from this approach have exhibited good agreement with experimental results as shown in Yuan et al. [113] and this work.

Following Yuan et al. approach, fire dynamic simulator (FDS) version 6.6 software was used to predict the effects produced by conveyor belt fires in different scenarios. FDS is a three-dimensional, large-eddy simulation model used for studying the evolution of fire, transport of gases, and smoke in enclosed spaces. FDS solves the governing equations using second order-accurate finite differences on a collection of uniformly spaced three-dimensional grids

[71]. FDS is the most widely used large-eddy simulation model in the fire science field since it has demonstrated good agreement with experimental results in validation studies[70].

The program models flame spread using a pyrolysis model alongside a gas phase combustion model. The pyrolysis model is in charge to simulate the decomposition of the belt material into the gas phase produced by a heat source. Then, the combustion model simulates the reaction between the gas phase and oxygen[70]. The pyrolysis and combustion processes are interdependent since the solid decomposition into the gas phase is produced by the heat transfer from the flame to the solid surface.

In order to model the pyrolysis process, FDS uses Equation 4.1 that represents the conversion rate of any multicomponent material (i) to a gas during the pyrolysis reaction. It is noteworthy that Equation 4.1 is valid as long as other materials do not produce material (i), and the residue and the reaction rate are not affected by the local oxygen volume fraction.

$$\frac{dY_S}{dt} = - \sum_{j=1}^{N_{r,i}} r_{i,j} \quad (4.1)$$

In the above equation,

$$r_{i,j} = A_{i,j} Y_{S,i}^{n_{S,ij}} \exp\left(-\frac{E_{i,j}}{RT_S}\right) \quad (4.2)$$

$Y_S = \frac{\rho_{S,i}}{\rho_o(0)}$ is the normalized density of the solid fuel, $r_{i,j}$ defines the rate of reaction of the i^{th} material undergoing its j^{th} reaction at the temperature T_S , $E_{i,j}$ reaction at the temperature T_S , E_{ij} is the activation energy (KJ/mol), R is the gas constant (J/mol.K), T is the temperature in which the reaction j^{th} occurs (K), $n_{S,ij}$ is the reaction order and $A_{i,j}$ is the pre-exponential factor (s^{-1}).

For a single material component, Equation 4.1 and Equation 4.2 can be simplified into

equation 4.3 and 4.4, respectively.

$$\frac{dY_S}{dt} = -r_{1,1} \quad (4.3)$$

$$r_{i,j} = A_{1,1} Y_{S,i}^{n_{S,1,1}} \exp\left(-\frac{E_{1,1}}{RT_S}\right) \quad (4.4)$$

As shown previously, to simulate the decomposition of the material, it is necessary to know the kinetic parameters such as pre-exponential factor (A) and the activation energy (E) associated to the pyrolysis. However, these parameters just mentioned are not easy to find or are unavailable for most of real materials [70]. Nevertheless, FDS can derive these values knowing the reference temperature (T_p) and the reference rate (r_p) through Equations 4.5 and 4.6 for a single material with a single component. Thermogravimetric analysis (TGA) is commonly used to obtain these two parameters in which the reference temperature (T_p) is defined as the “temperature at which the mass loss rate curve from a TGA test peaks”, and the reference rate (r_p) is defined as “the value of peak mass loss rate” [70].

$$E_{1,1} = \frac{er_p RT_p^2}{\beta} \quad (4.5)$$

$$A_{1,1} = er_p e^{\frac{E}{RT_p}} \quad (4.6)$$

In this study, it was assumed that the conveyor belt is made of styrene-butadiene rubber (SBR) since, it is a polymer widely used for the fabrication of conveyor belts in the mining industry providing excellent abrasion and heat resistance [43]. According to TGA results published by Yuan et al.[113] and Grieco et al.[37], SBR is a material with multiple compo-

nents. Yuan et al.[113] observed in TGA results that SBR is made up of two components. A first component associated to a first peak evidenced at 232°C and reference rate equal to 0.0058 s⁻¹. This peak was elongated and narrow, and it represented the mass loss rate from 97% to 89%. The second peak, associated with the second component, was seen at 469°C and reference rate of 0.0022 s⁻¹. This second peak was wider and shorter than the first peak and represented the mass loss rate from 80% to 40%. On the other hand, Lin and Chang[61], in a study carried out using rubber waste composed of SBR, reported three components. The first, second and third peaks associated with each component were evidenced at 307°C, 447°C, and 597°C, respectively. However, Lin and Chang[61] concluded that the fraction of volatile matter produced by the third component is less than 15%. As can be seen in these TGA studies, the contribution for volatile matter production can be attributed to mainly the two first components with reference temperature around 250°C and around 450°C. Although main variables such as reference rate and reference temperature for the two main components of SBR are known properties, respective pyrolysis residues are difficult to obtain [113]. For this reason, Yuan's approach [113] proposed and demonstrated that SBR can be modeled as single component material in which only a reference temperature and reference rate are needed. Under this premise, it is assumed that SBR has an unique peak in the TGA analysis. This peak is expected to be between the first and second peaks associated with the components reported in the two studies mentioned previously.

In order to determine the reference temperature (T_p) and the reference rate (r_p) for the assumed single component of SBR, the model calibration was performed. The kinetic parameters were obtained by matching flame spread rates in both simulation and experimental results available in the literature during the calibration. Different reference temperatures (between 232°C and 469°C) and reference rates (between 0.0022 s⁻¹ and 0.0058 s⁻¹) inside the interval of the peaks of the first two components mentioned previously were

tested. A heating rate equals to 20 °C/min used in the TGA analysis carried out by Yuan et al.[113] was set as input for the pyrolysis model.

The heat of combustion and gasification of the SBR used for the numerical simulations were 28,500 kJ/kg and 1,500 kJ/kg, respectively. These values correspond to the fire-resistant SBR belt reported by Tewarson[96]. The heat of combustion for pure propylene is 48,902 kJ/kg, as reported by Wiberg and Fenoglio[107]. In order to avoid discrepancy with the SBR heat of combustion, FDS adjusts the mass loss rate of fuel gas to produce the expected heat release rate. Nevertheless, the mass of SBR is reduced according to the value of parameters established in the pyrolysis model [70].

The percentages of volatile matter and char material produced during the pyrolysis process were set to 63% and 37% based on the values reported by Grieco et al.[37], respectively. Also, in the same study, the components of volatile matter produced during pyrolysis of SBR were reported. This composition is shown in Table 4.3, in which the gas-mixture is composed of seven different gases. The percentage of molar fraction for each gas is also showed in Table 4.3. However, it is important to mention that in FDS only one gaseous fuel can be in the combustion reaction. McGrattan et al.[70] recommend using the most predominant burn gaseous fuel. Thus, propylene was the gas selected.

For the determination of some of the tenability parameters discussed in a following section, the post-combustion yields of CO (Y_{CO}) and soot (Y_{soot}) were determined. Y_{CO} and Y_{soot} are defined as the fraction of fuel mass converted into carbon monoxide and smoke particulate, respectively. These values are reported in literature based on the mass of SBR material burned. Thus, considering the heat of combustions of SBR and propylene, only a fraction of 0.58 of the expected amounts of CO and soot are really released during simulations, since in FDS, the mass loss rate of fuel gas is adjusted to produce the expected HRR [70]. In order to make up for the reduced production of CO and soot, and follow a conservative approach,

Table 4.3: Mole fractions of volatile matter composition during pyrolysis of SBR[37].

Name	Formula	Mole fraction(%)
Carbon Dioxide	CO_2	2.578
Ethylene	C_2H_4	17.138
Ethane	C_2H_6	7.623
Propylene	C_3H_6	26.26
Propane	C_3H_8	10.371
Hydrogen	H_2	17.205
Methane	CH_4	18.825
Carbon Monoxide	CO	18.825

Table 4.4: Properties of SBR and Charring material used in numerical simulations.

Property	SBR	Charring
Density (Kg/m ³)	1300[65]	600[65]
Specific Heat (kJ/Kg K)	1.3[65]	0.6[65]
Conductivity (W/m K)	0.19[65]	0.09[65]
Heat of combustion (kJ/Kg)	28500[96]	-
Heat of gasification (kJ/Kg)	1500[96]	-
Volatile matter (%)	63[37]	-
Char material (%)	-	37[37]
Y_{CO}	0.12[97, 111]	-
Y_{Soot}	0.11[60]	-

upper limits of ranges of these parameters proposed in literature were selected. The amount of carbon monoxide produced during the combustion of SBR increases as a function of the equivalence ratio (ϕ) according to Equations 4.7 [97]. Yuan et al.[111] concluded that flame spread typically occurred for $\phi > 1$ (fuel rich combustion). Thus, a conservative value for CO yield (Y_{CO}) was set to 0.12 for ϕ equals to 1.25. The value of soot yield (Y_{CO}) produced during a fire of a SBR tire was reported within a range of 0.03 and 0.11 [60]. For this study, a soot yield of 0.11 was considered following a conservative approach for firefighters. A summary of properties of SBR and charring material used in the numerical simulations are shown in Table 4.4 [65, 96].

$$Y_{CO} = 0.072(1 + 2.5\exp(-2.5\phi^{-2.8})) \quad (4.7)$$

4.5 Numerical details for model calibration and validation

Two different CFD domains (A and B) of conveyor belt entries were built to calibrate and validate the CFD model, respectively. As mentioned previously, model calibration and validation were performed in this study to determine some required input parameters for modeling and verify the CFD model capacity of predicting realistic results.

Figure 4.2-A shows the cross section of CFD Domain A that was used for model calibration and built based on the geometry of the fire tunnel used by Lazzara and Perzak[53]. In this experimental test, flame spread rate was measured for different air velocities. Although the cross sectional area of the CFD domain and tunnel were the same 7.6 m², the cross sectional shapes were slightly different, since in FDS, it is not possible to have non-rectangular geometries [70]. CFD Domain A was 2.0 m high and 3.8 m wide. The conveyor belt was in the center of the mine entry 1.4 m off the right and left walls. Thermocouples were spaced 1.0 meter apart from each other on the belt surface in order to determine the flame position over time as well as the flame spread rate for different air velocities. The flame position was determined where the belt surface reached 391°C. This temperature was reported as the piloted ignition temperature for the SBR belt meaning that SBR breaks down to volatile fuel at a rate enough to maintain a flammable mixture [65].

The CFD Domain B shown in Figure 4.2-B was used for model validation and built based on the tunnel in which the experimental test of Yuan et al.[113] was carried out. CFD Domain

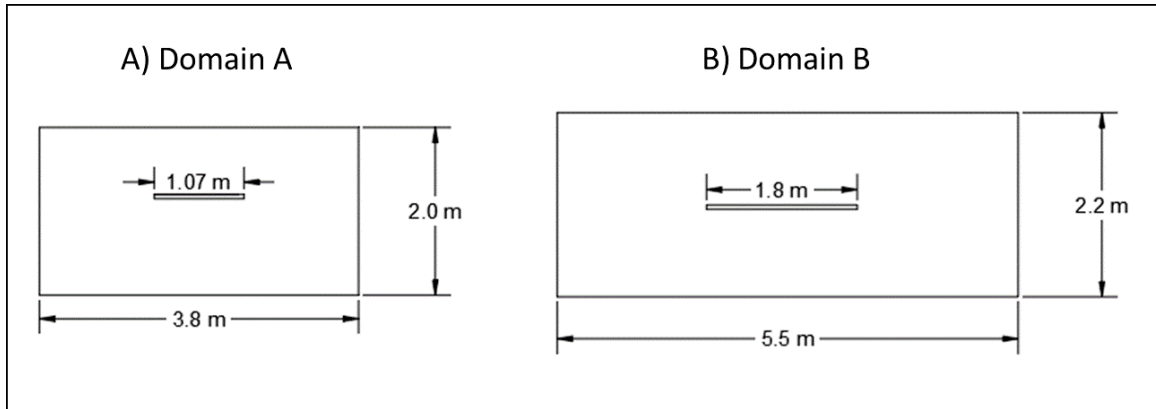


Figure 4.2: Cross section of: A) Domain A, B) Domain B.

B was used to determine the fire HRR and belt surface temperatures in order to be compared with the experimental and numerical results reported by Yuan et al.[113]. CFD domain B was 2.2 m high and 5.5 m wide. The conveyor belt was located at the center of the mine entry 1.85 m away from the right and left wall. The mean air velocity was set to 1.5 m/s as used in the experiment.

Virtual heater elements were located close to the conveyor belt in order to simulate hot spots that trigger the decomposition of the belt material in both CFD domains. For the numerical simulation, an ignition source is not needed, since FDS assumes that once the fuel gas and the oxygen are in contact, the combustion reaction starts [70]. The virtual heaters were set at $1,600^{\circ}\text{C}$, providing around 7.0 kW each, since the ignition heat for SBR was estimated around 14 kW [111]. Virtual heaters were maintained turned on during the flame spread since they were used to simulate the coal fire that usually ignites the conveyor belt and remains active during the this process. The belt conveyor was located 4.0 m from the tunnel inlet with a belt thickness of 15 mm.

4.5.1 Grid analysis, model calibration, and validation

During model calibration, different reference rates (between 0.0022 s^{-1} and 0.0058 s^{-1}) and reference temperatures (between 232°C and 469°C) were used. Model calibration was stopped once the mean of absolute error for model flame spread predictions calculated using Equation 4.8 was lower than 0.5 cm/s . Experimental results reported by Lazzara and Perzak [53] were used for the calculation of this error. A grid size of 0.1 m was used since Yuan and others [113] reported good agreement when this grid was used to simulate flame spread over conveyor belts. The lowest average absolute error equal to 0.47 cm/s was obtained for a reference value equal to 0.0022 s^{-1} and reference temperature equal to 368°C . Figure 4.3 shows the flame spread rate for different air velocities obtained from model using the 0.1 m grid and reported by Lazzara and Perzak[53]. It can be seen that numerical values obtained using this grid size and experimental values are in good agreement for the range of velocity between 0.8 m/s and 4.1 m/s . The model can reproduce the behavior of the flame spread rate peaking at 1.5 m/s and then decreasing for greater air velocities. Despite the good agreement between numerical and experimental results using a 0.1 m grid, flame spread rate was also calculated using a finer grid equals to 0.05 m . This was performed to evaluate if the proximity between results was an instance where the modeling uncertainties cancelled out since it was considered a 0.1 m grid relatively coarse to reproduce the flame adequately. Furthermore, as the objective of this paper was to predict fire conditions upwind from the fire, HRR (a variable with high influence on fire conditions), visibility, and temperature were also calculated using both grids in Domain A for scenarios with air velocities between 1 and 3 m/s . This velocity range was the one used to develop the conveyor belt fire classification model as shown in a following section.

$$E_{Param,g} = |Param_{exp} - Param_{model,g}| \quad (4.8)$$

Where $E_{Param,g}$ is the absolute error for parameter prediction using a grid size g , $Param_{exp}$ is the value of the parameter reported in the experimental test, and $Param_{model,g}$ is the value of the parameter predicted by the model using a grid size g .

Flame spread results obtained using the fine grid are shown in Figure 4.3. Figure 4.4 shows the HRR, visibility, and temperature using both grids for scenarios with air velocity equals to 1.5, 2.0, and 2.5 m/s. Results of visibility and temperature were calculated at an attack position 3 m away from the fire and at height 1.5 m from the floor. The mean of absolute error for model flame spread predictions calculated using Equation 4.8 for both grids ($\overline{E}_{FSR,Coarse}$ and $\overline{E}_{FSR,Fine}$) are shown in Table 4.5. The mean of percent error of the maximum HRR ($\overline{PE}_{HRR}$) and temperature ($\overline{PE}_{Temp}$), and the minimum value of visibility ($\overline{PE}_{Vis}$) predicted by the model using the coarse grid when compared with predictions using the fine grid are shown in Table 4.5. Coarse grid error percent of the parameters mentioned were calculated using Equation 4.9.

Two observations can be noticed from these grid analysis results. First, the mean of absolute error for model flame spread predictions was not reduced when the fine grid was used, indicating that the agreement between coarse grid simulation and test results could be an instance where the uncertainties are cancelled out; however, flame spread rate behavior and most of its values predicted were consistent with experimental results. Due to its approximation in the reproduction of flame spread phenomenon, this approach could be used for estimation of conditions during belt fires as also suggested by Yuan et al. [113]. Second, HRR, temperature, and visibility percent error means were lower than 10% for the coarse grid when compared with results using the fine grid showing an acceptable convergence.

Considering that the objective of this paper is not focused on resolving the flame spread to sufficient detail but predicting fire conditions, this approach with a grid size of 0.10 m and calibrated parameters is recommended to be used for fire condition predictions as long as it

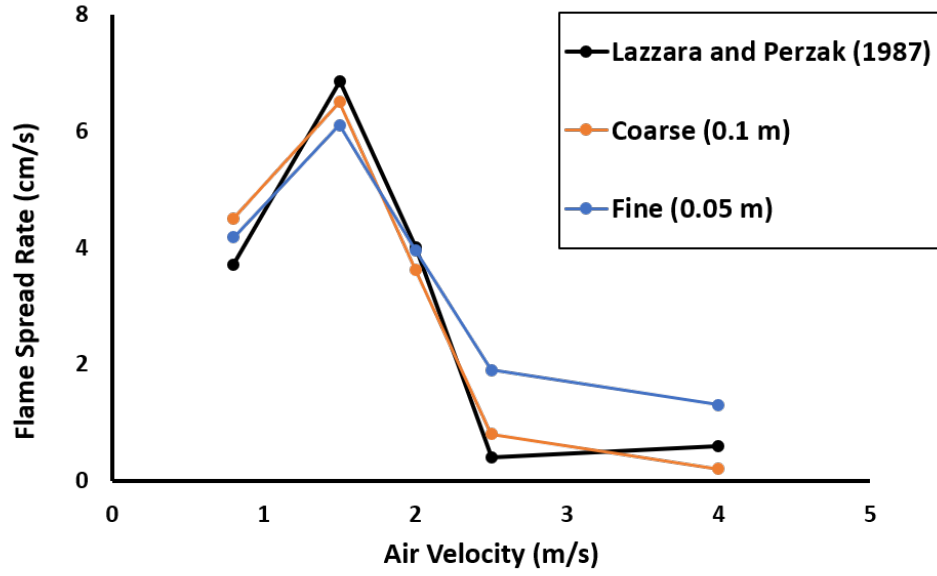


Figure 4.3: Comparison of flame spread rate for different air velocities determined by the calibrated model using the coarse and fine grids in Domain A, and Lazzara and Perzak[53] in an experimental test.

can be validated. This recommendation is based on the coarse grid percent error is lower than 10% and hundreds of simulations are required for any parametric study.

$$PE_{Param} = \frac{|Param_{model,c} - Param_{model,f}|}{Param_{model,f}} * 100 \quad (4.9)$$

Where, PE_{Param} is the percent error of parameter predicted by the model using the coarse mesh. $Param_{model,c}$ and $Param_{model,f}$ are the value of parameter predicted by the model using the coarse and fine grids, respectively.

In order to test the calibrated model capacity predicting fire conditions, a model validation was performed. A numerical simulation was performed in the CFD Domain B in order to compare numerical results with experimental values of the fire HRR and belt surface temperatures reported by Yuan et al.[113]. The Fire HRR evolution in the simulations

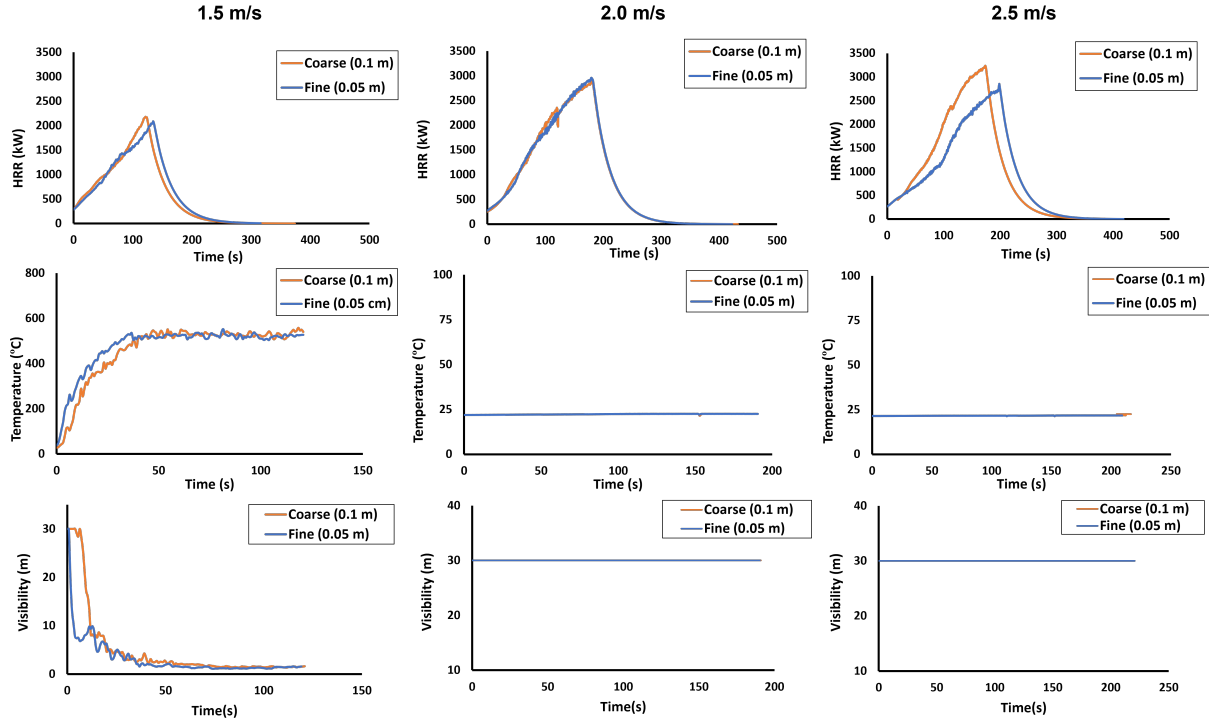


Figure 4.4: HRR, visibility, and temperature results using both grids in the CFD Domain A for different air velocities.

Table 4.5: Summary of results of grid analysis, model calibration, and validation.

Parameter	Value	units
$\overline{E}_{FSR,Coarse}(calibration)$	0.47	cm/s
$\overline{E}_{FSR,Fine}$	0.79	cm/s
$\overline{PE}_{HRR}$	6.07	%
$\overline{PE}_{Temp}$	1.53	%
$\overline{PE}_{Vis}$	0	%
$\overline{PE}_{HRR}(validation)$	7.04	%

and experiment after the onset of the flame spread is shown in Figure 4.5. The maximum HRR was around 7,600 kW and 8,000 kW in the experimental test reported by Yuan et al. [113] and models, respectively, and it was reached at 400 s after the beginning of flame spread. The percent error of the maximum HRR predicted by the model when compared with experimental results was 7.04% which indicated an acceptable agreement. However, FDS models seem to underestimate the HRR during the growth stage. In addition to the HRR, comparison of surface temperatures between test and model reported in Yuan et al.[113], and results of the calibrated model was performed as shown in Figure 4.6. Figure 4.6 shows the belt surface temperatures at two positions from belt front. Simulation results of the calibrated model regarding the evolution of temperature at 6 m from the belt front show good agreement with experimental and yuan model values. Nevertheless, some discrepancy can be seen at 3 m from the belt front with experimental values. Despite these discrepancies, the range of temperature values is the same.

Based on these results, it can be stated that the proximity between model predictions and experimental values allow to validate the calibrated model using a 0.1 m grid. Model validation is accepted since the main objective of this paper is to determine fire conditions produced by the belt fires in which the HRR has the highest influence. However, it is noteworthy that the almost exact match between the calibration case using the coarse grid (0.1 m) and experimental results of flame spread rate could be an instance where the uncertainties are cancelled out. This is demonstrated with the poor agreement between test and model in belt surface temperature at 3 m from belt front, the fire growth stage in the validation case (see Figure 4.5), and results of flame spread using a finer grid. These facts indicate that the approach used has limitations reproducing the flame spread phenomenon due to the lack of physics in the model even though finer grid is used to resolve the flame more adequately. Thus, it is recommended to use this approach for prediction of fire conditions produced by

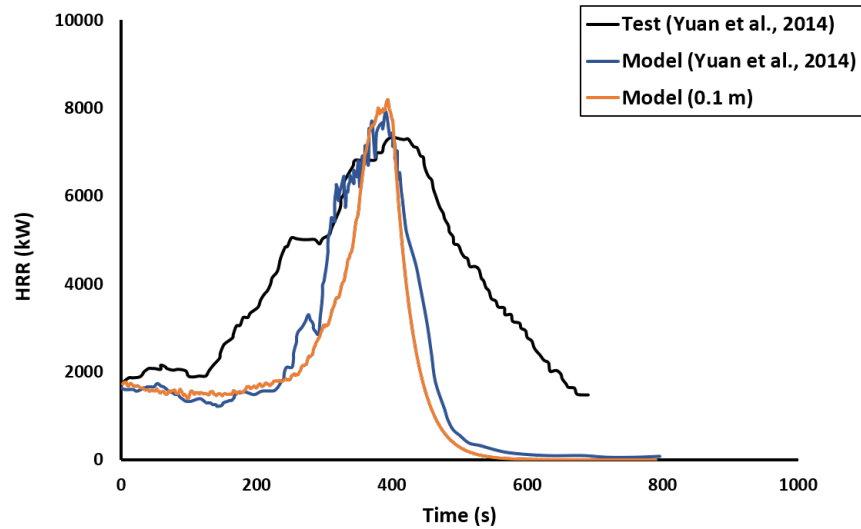


Figure 4.5: Comparison of heat release rate (HRR) between the calibrated model in Domain B and results reported by Yuan et al.[113].

flame spread over conveyor belts; however, more development is needed on this approach for studying flame spread over conveyor belts with certainty.

4.6 Conveyor belt fire model

A CFD domain similar to belt entries of partner mines as shown in Figure 4.7 were used to study the effects of fire spreading over conveyor belts on underground conditions. The domain width and height were varied between 4.0 m – 7.0 m and 1.8 m -2.8 m, respectively. The domain length of 26.0 m was maintained constant. The conveyor belt was located 1.0 m off the right wall. The conveyor belt surface was 23.0 m long, 1.8 meters wide, and was composed of SBR. The kinetic parameters obtained during the calibration and properties of SBR shown in Table 4.4 were used in these numerical simulations. The walls were composed of coal with thickness of 0.10 m. Pittsburgh coal properties such as density, conductivity, specific heat and emissivity were used and set to 1,323 Kg/m³, 0.214 W/mK, 1.66 kJ/KgK,

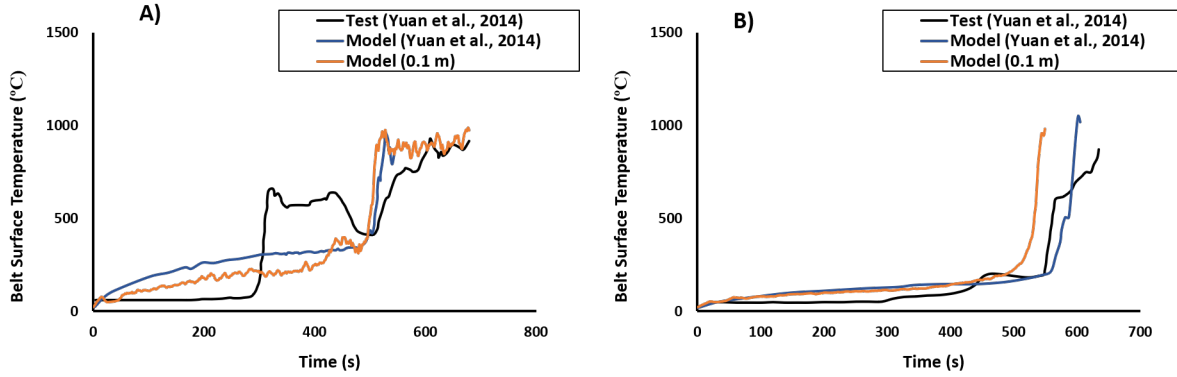


Figure 4.6: Comparison of surface temperatures between test and simulations: A) 3 m from belt front, B) 6 m from belt front.

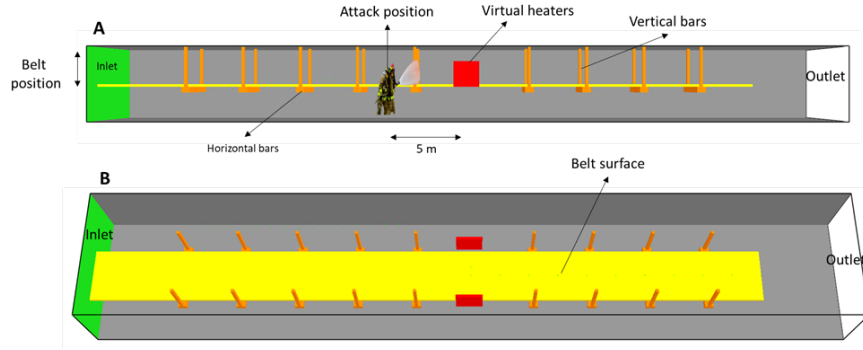


Figure 4.7: CFD domain of conveyor belt: A) side view B) Top view.

and 0.96, respectively [92]. The conveyor belt structure consisted of horizontal bars attached to vertical chains hooked to the roof as shown in Figure 4.7. Horizontal bars were 2.4 m long. The vertical chains and horizontal bars were spaced 2 m from each other. The chains and horizontal bars were assumed to be made of steel. Steel property values of 0.85, 8,050 Kg/m^3 , 45.8 W/K and 0.46 kJ/KgK were set as emissivity, density, conductivity and specific heat[34], respectively. As in the simulations used for calibration, the fire was ignited by virtual heaters located next to the conveyor belt. Virtual heater dimensions were 0.9 m long and 0.9 m wide. They were also set to $1,600^\circ\text{C}$ during the flame spread.

According to the Title 30 CFR § 75.350 (b)(7), the minimum air velocity in the belt entry

Table 4.6: Parameters varied during scenarios for the determination of effects of belt fires on underground firefighters.

Parameters	Range
Air velocity (m/s)	1.0-3.0
Belt position (m)	0.5-1.5
Height (m)	1.8-2.8
Width (m)	4.0-7.0

must be 0.5 m/s and must not exceed 5.0 m/s [101]. Previous studies have shown that air velocity and belt position contribute to the heat transfer along the mine entry, influencing the flame spread rate, heat release rate produced by the fire [25, 111], and consequently the underground conditions. For this reason, air velocity was varied between 1.0 m/s and 3.0 m/s and belt position between 0.5 m and 1.5 m. Belt position is defined as the distance between the belt surface and the mine entry roof. The range of parameters varied in simulations are shown in Table 4.6.

4.7 Fire classes and exposure limits

Four parameters such as temperature, visibility, radiation, and toxicity are normally investigated during tenability analysis to determine the conditions for firefighting personnel [33, 39, 45, 78]. In this study, scenarios in which conditions remain tenable for direct attack, and scenarios which human life cannot be supported and indirect attack is required were determined. A tenable environment refers to a location where none of the exposure limits have been exceeded. Thus, two different types of belt fires were proposed in this study as shown in Table 4.7.

Generally, in underground coal mining, firefighting activities are carried out by two groups. The first group is the first responder group composed of bare-faced personnel that works

Table 4.7: Description and recommendation for each type of fire.

Fire Type	Description
Type I	Direct attack is recommended.
Type II	Remote attack is recommended.

daily in the mine. The second group is the second responder group mainly composed by the fire brigade [18]. For this study, it was only considered the second responder group for the model elaboration and parameters analysis. It is noteworthy that the members of this group carry breathing apparatus (SBCAs), have specialized firefighting tools, and wear fire resistant clothing [18]. Thus, toxicity elements such as combustion gas concentrations (CO and CO_2) and oxygen (O_2) concentration were not accounted for them since they have breathing apparatus and it has been demonstrated that exposure limit for temperature, radiation and visibility are first exceeded than toxicity during fire scenarios [33, 39].

In the course of this study all exposure limits were considered as ceiling limits in order to follow a conservative approach. As recommended by Haghighat and Luxbacher[39], exposure limits for temperature and radiant heat were set to 100°C and 5.0 kW/m^2 for the second responder group, respectively. For purposes of this work, the ceiling limit for visibility was set to 5 m. It is noteworthy that visibility is the most subjective criteria; however, Gehandler[33] proposed this visibility limit for firefighting personnel who knows the environment where the fire occurs. The visibility limit is usually determined based on the relationship between walking speed and visibility [30, 31]. In FDS the maximum visibility was set to 30 m and optical coefficient (C) was set to 3 assuming light reflecting steel chains and reflecting signs hanging on belt entry walls. A summary of ceiling limits for the parameters used in this study are shown in Table 4.8.

Table 4.8: Ceiling limits for the different parameters

Fire Type	Description
Heat flux (kW/m ³)	< 5.0[39]
Temperature (°C)	< 100[39]
Visibility (m)	> 5[33]

4.8 Neural Networks

ANNs were used in this study to determine the effects of parameters on conditions at the attack position and elaborate the classification model. Each ANN used in this study was trained using stochastic gradient descent solver (SGD). The maximum number of iterations allowed during training was 4000. The loss function used in training was Cross-entropy. Logistic function was used as activation function for hidden layers. To determine the best architecture for each case, cross validation (CV) and mean classification accuracy metric were used. Architectures tested for each ANN are shown in Table 4.9. All network structures were composed of one input layer, one output layer and one or two hidden layers depending on the architecture. It is important to say that L2-norm regularization technique was used with an alpha parameter equals to 0.5 to avoid overfitting in the margins provided by ANNs for fire classification. For illustration purpose, architecture “Arch6” is shown in Figure 4.8 in which the first hidden layer was composed of 2 units and the second hidden layer was composed of 4 units. The number of units in the input layer can vary depending on the number of input parameters used as it will be showed in following sections. Architectures were built using Scikit-learn that is a free software machine learning library for the python programming language [89].

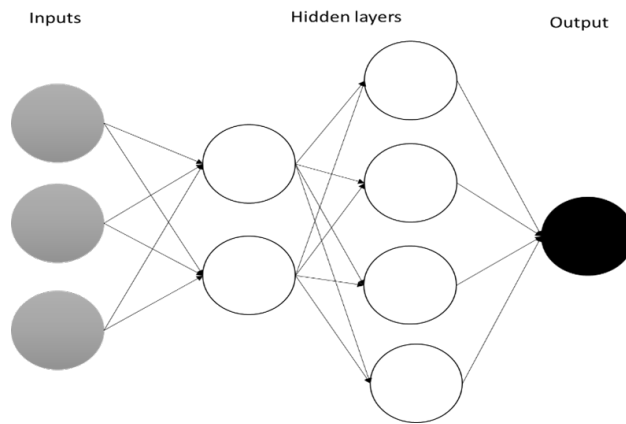


Figure 4.8: Arch6 architecture

Table 4.9: ANN Architectures

Parameters	Hidden Layers	Units in each hidden layer
Arch1	1	[1]
Arch2	1	[2]
Arch3	1	[4]
Arch4	1	[8]
Arch5	2	[2,2]
Arch6	2	[2,4]
Arch7	2	[4,4]

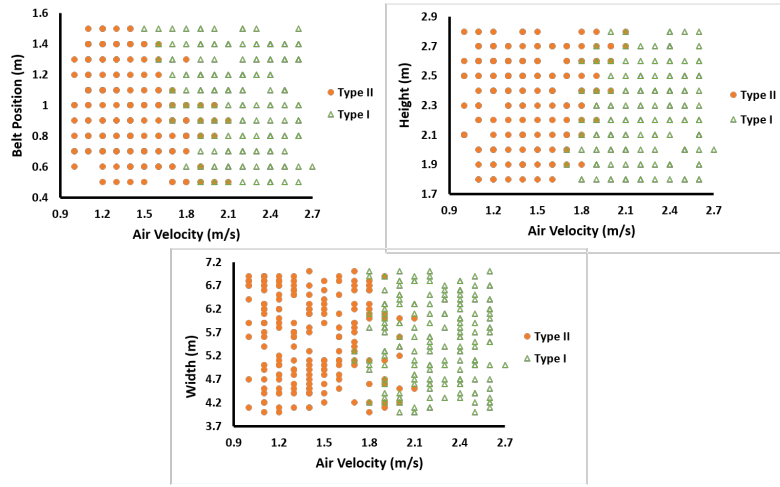


Figure 4.9: Classification of fire scenarios with respect to design parameters.

4.9 Results and discussion

400 CFD scenarios were simulated to determine the conveyor belt fire classification model and effect of parameters such as air velocity, belt position, tunnel height, and width on the fire classification. The values of input parameters for each unique scenario were obtained using simple random sampling from uniform distributions. This means that each value within a range had the same probability of being chosen during the sampling process. For the determination of the fire type in each scenario, tenability parameters shown in Table 4.8 were calculated at an attack position 5 m upwind from the fire at intervals of 1 second during 900 s. As mentioned by Mcpherson[74], the attack position for underground coal mine fires can be up to 10 meters away from the fire and it is totally dependent on the mine entry height. For this study, an attack position of 5 m upwind from the fire seems reasonably for the range of tunnel heights simulated. On the other hand, it was considered that firefighting personnel would try to crouch when they approach and attack the fire with the objective to stay below the smoke layer as also was assumed by Haghghatand Luxbacher[39]. Thus, tenability parameters were determined at a height of 1.5 m from the floor.

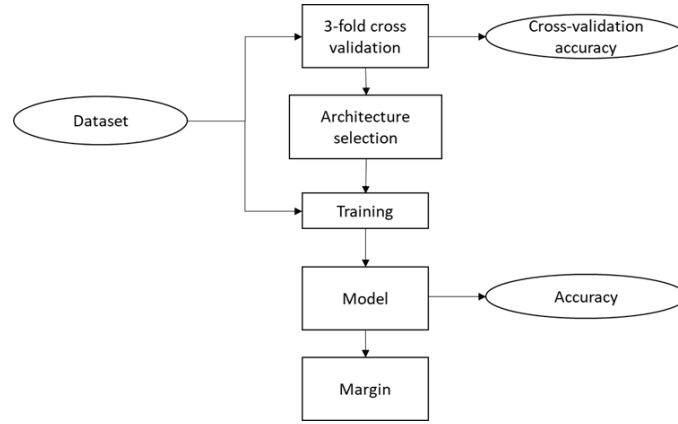


Figure 4.10: Methodology for the determination of the best model, training, and validation accuracies for each ANN.

Simulation results were compared with the tenability limits allowing for the fire classification of each scenario as shown in Figure 4.9. In Figure 4.9 graphs, each point represents a scenario in which green triangles correspond to fire Type I and orange dots correspond to scenarios classified as Type II. In these graphics, air velocity was plotted along x-axis and compared with the other three parameters since it is the variable with the highest influence on the fire classification as discussed later. Most of Type I and Type II fires are located on the right and left sides of the plots, respectively. However, more overlapping between fires Type I and Type II at the center of the plot can be seen when tunnel width was plotted, indicating a possible negligible influence on the fire classification. In order to determine the influence of the four parameters on the fire classification, seven ANNs were used. The first four ANNs were utilized to determine the influence of each parameter individually. Subsequent, the second three ANNs were implemented to determine the effects of parameters when combined with air velocity. After all, a final ANN was implemented in which the input parameters were the ones with the highest influence on the fire classification allowing for the determination of the conveyor belt fire classification model.

In order to determine the effect of parameters on fire classification, ANNs were training

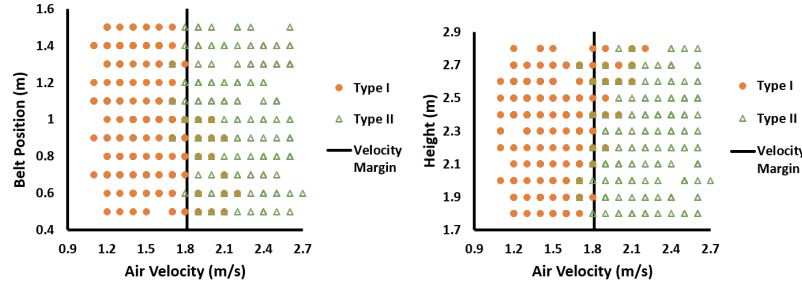


Figure 4.11: Velocity margin provided by ANN-00.

using the entire dataset. As mentioned previously, different architectures were evaluated. The architecture with the highest CV accuracy was selected in each case. The methodology used for determining the effect of parameters on fire classification is shown in Figure 4.10. In this methodology, 3-fold CV was carried out in order to select the best architecture. Once the architecture was selected, the ANN was trained to determine accuracy and the classification margin allowing for the determination of parameters effect on fire classification.

Air velocity was used as input parameter in ANN-00. The highest CV accuracy of 88.73% was obtained for Arch1 and an accuracy of 89.00% for the entire dataset as shown in Table 4.10. This indicates that only using air velocity as input parameter, ANN-00 was able to classify 356 out of 400 samples correctly suggesting that air velocity can explain around 89 percent of the variability on fire classification. An architecture with a single input parameter indicates that a value of velocity is determined by ANN-00 to separate fires Type I and II. To find this velocity value, 1000 velocities within the velocity range of scenarios used for training were fed into ANN-00. Then, the probability of each velocity of being Type I and II was determined. The velocity with probability equals to 0.5 of being both fire types was determined as the dividing point between fire Types I and II. This dividing point was determined to be located at 1.81 m/s. A margin equals to this velocity in 2D plots is shown in Figure 4.11. Based on Figure 4.11, the critical velocity of a belt fire can be estimated to be between 1.5 m/s and 2.2 m/s for the scenarios simulated in this paper. Scenarios classified

Table 4.10: Networks' architecture and accuracy.

Name	Input parameters	Architecture	C-V Accuracy (%)	Accuracy (%)
ANN-00	Velocity	Arch-1	88.73	89.00
ANN-01	Belt position	Arch-1	58.57	57.03
ANN-02	Height	Arch-2	61.64	60.87
ANN-03	Width	Arch-2	57.06	51.15
ANN-1	Velocity, Belt position	Arch-6	92.32	92.07
ANN-2	Velocity, Height	Arch-6	92.08	92.07
ANN-3	Velocity, Width	Arch-7	88.24	88.50

Type II within this critical velocity range exhibited fire sizes around 8000 kW. Applying Thomas correlation shown in Equation 4.10 [98, 99] with Froude number equals to 4.5 as proposed by Danziger and Kennedy[19] and Kennedy[46], the critical velocity was calculated to be around 1.6 m/s which indicates proximity between results obtained in this study and Thomas[98, 99] approach. However, some discrepancies can exist since the effect of the belt structure is not considered in the empirical correlation.

$$V_c = \left[\frac{gQ}{\rho_o C_p \left(\frac{Q}{\rho_o C_p H V_c} + T_o W \right) A F r_c} \right]^{1/3} \quad (4.10)$$

In the above equation, Q is the heat release rate of the fire (kW), V_c is the critical velocity (m/s), ρ_o is the ambient density Kg/m³, C_p is the air specific heat (kJ/kg K), T_o is the ambient temperature (K), W is the tunnel width (m), A is the cross-sectional area of the tunnel (m²), Fr_c is the critical Froude number.

Belt position, tunnel height and tunnel width were also used as individual input parameters for ANN-01, ANN02, and ANN03, respectively. As shown in Table 4.10, the accuracies for this three ANNs were 57.03%, 60.87%, and 51.15%, respectively. These values of accuracies reflect that these parameters by itself have a negligible influence on the fire classification. However, a synergistic effect could occur when they are combined with air velocity. For

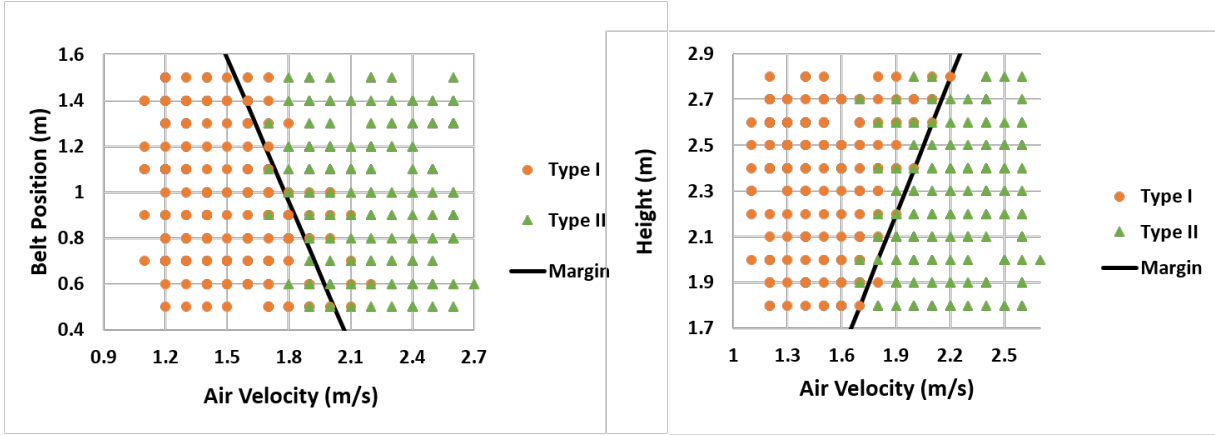


Figure 4.12: Margins provided by ANN-1 and ANN-2.

this reason, to determine the effects of each parameter when combined with air velocity, ANN-1, ANN-2, and ANN-3 were used. As shown in Table 4.10, accuracies for ANN-1 and ANN-2 improved in comparison with ANN-00. However, similar accuracies between ANN-00 and ANN-3 were obtained indicating insignificant influence of tunnel width on the fire classification. Because of this fact, tunnel width was not considered as input for the belt fire classification model. This result agrees with results obtained by Li and Ingason[58] in which it was concluded that for large fires, the critical velocity is independent of tunnel width.

In order to define the effect of belt position and tunnel height when combined with air velocity on fire classification, 2D margins were determined. Probability estimates of 1000 scenarios inside of the intervals of air velocity and belt position, and air velocity and tunnel height were calculated using ANN-1 and ANN-2, respectively. Scenarios with probabilities equal to 0.5 were assumed to be on the margins. Margins provided by ANN-1 and ANN-2 are shown in Figure 4.12, respectively. It is worth of mentioning that the 0.5 probability points provided by ANN-1 and ANN-2 were fitted to linear trendlines.

The equation of margin provided by ANN-1 with a R-squared of 1.0 is shown in Equation 4.11. This margin indicates that as belt position decreases, longitudinal air velocity must be

greater in order that fires are classified as Type I. In other words, the lower is the distance between the mine roof and conveyor belt surface, the higher must be the air velocity in order to avoid that tenability limits are exceeded due to presence of rollback. This fact can be attributed to the radiation of heat to the belt surface. With lower surface to roof distance, roof would have a higher temperature and would radiate more heat back increasing belt burning rate, fire size, and fire buoyancy force which could increase the amount of smoke upwind from the fire when inertial forces generated by ventilation are not high enough. This explanation agrees with a study carried out by Yuan et al.[111] in which it was found that for lower surface-to-roof distances, the flame spread rate was greater and, conditions for fire development and growth were better due to more heat radiation from roof and belt. Additionally, small separations between the roof and belt surface limits the accessibility of oxygen to the flame leading to a combustion within the fuel-rich region where more rapid flames and high smoke production are observed [111].

$$BP = -2.04V + 4.69 \quad (4.11)$$

$$H = 1.99V - 1.35 \quad (4.12)$$

In the above equations, BP is belt position (m), V is air velocity (m/s), and H is tunnel height (m).

To visualize the effects of belt position on fire classification and fire intensity, simulation results of smoke layer and HRR for two scenarios named as A and B are shown Figure 4.13 and Figure 4.14, respectively. Both scenarios have the same air velocity and tunnel height, but different belt position as shown in Table 4.11. For scenario A can be seen the presence of

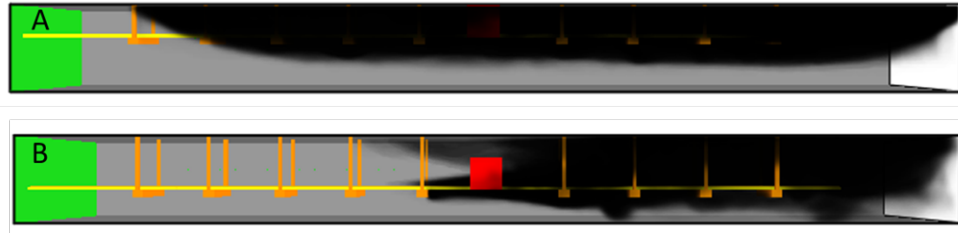


Figure 4.13: Smoke in Scenarios A and B after of the onset of the flame spread.

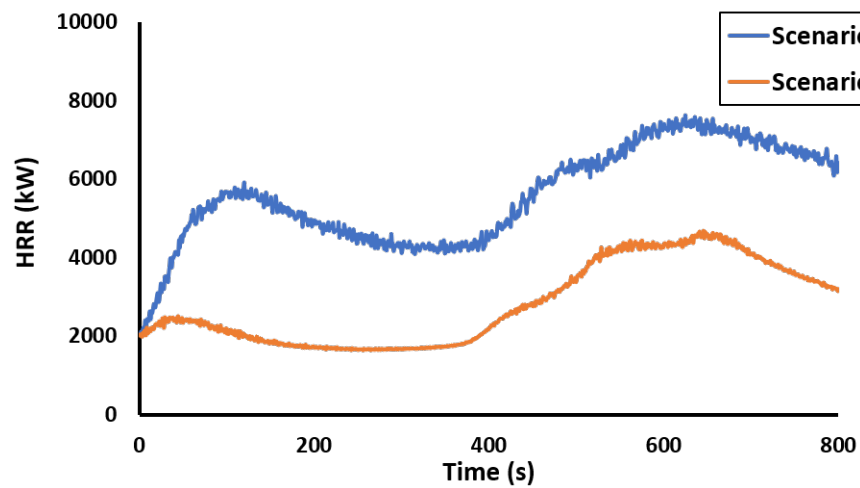


Figure 4.14: HRR for Scenario A and B.

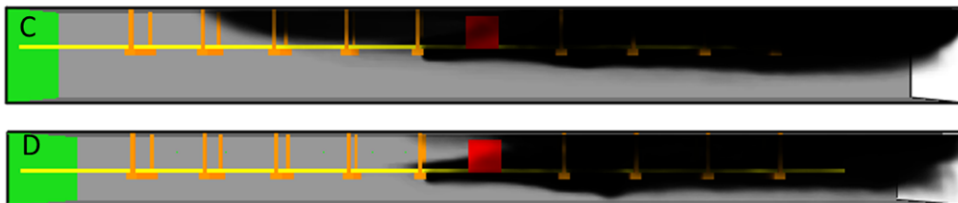


Figure 4.15: Smoke in Scenarios C and D after 600 s of the onset of the flame spread.

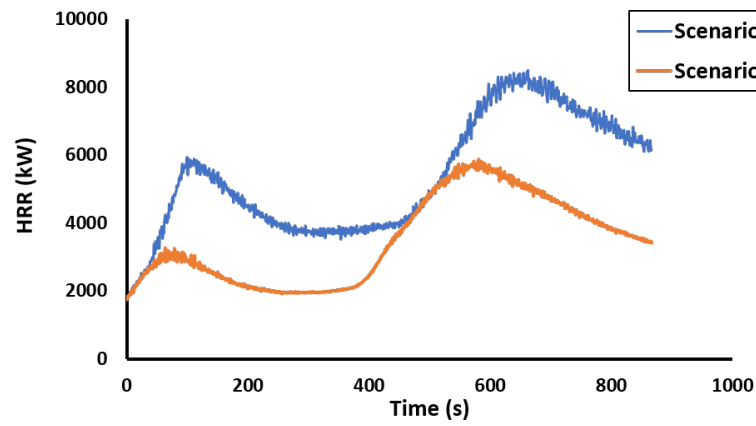


Figure 4.16: HRR for Scenario C and D.

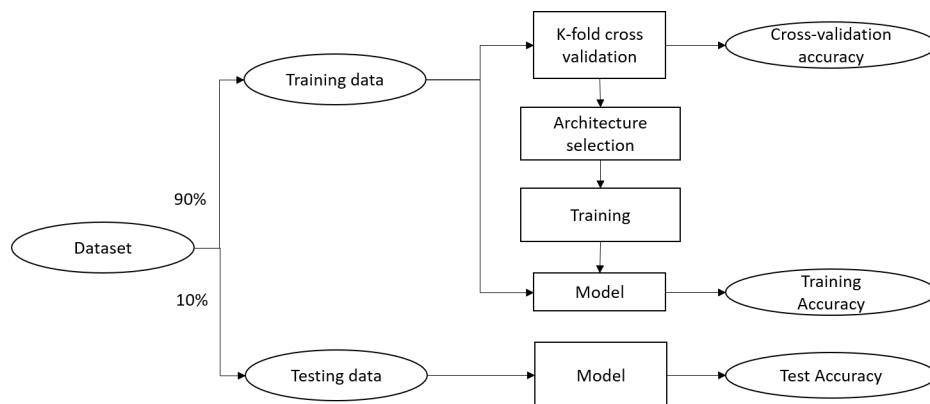


Figure 4.17: Methodology for model determination.

Table 4.11: Input parameters for scenario A and B.

Scenario	A	B
Air Velocity (m/s)	1.8	1.8
Tunnel Height (m)	2.4	2.4
Belt position (m)	0.8	1.4

rollback which allows for a non-tenable scenario classified as Type II. Figure 4.14 shows the maximum fire size and fire size values over time are greater in Scenario A than in Scenario B due to the proximity of the belt surface to the roof. In Scenario A, the buoyancy force generated by a larger fire overcomes the inertial forces generated by the ventilation with an air velocity of 1.8 m/s. Contrary, in Scenario B the ventilation is able to keep the smoke away upwind from the fire due to a smaller fire size being classified as a scenario Type I.

The equation of margin provided by ANN-2 with a R-squared of 1.0 is shown in Equation 4.12. This margin shows that as tunnel height increases, air velocity must be greater for fire scenarios to be classified as Type I as shown in Figure 4.12. This turns out that the longitudinal air velocity must be greater for taller tunnel heights in order to avoid rollback. This result agrees with a study carried out by Li and Ingason[58] in which it was found that the critical velocity considerably rises as tunnel height increases. The influence of tunnel height on fire classification and fire intensity can be seen when scenarios C and D are compared. Parameters of scenarios C and D are shown in Table 4.12. Rollback is seen for Scenario C with greater tunnel height while for scenario D there is not smoke upwind from the fire, as shown in Figure 4.15. HRR for scenario C and D is shown in Figure 4.16. As was seen for belt position analysis, tunnel height also impacts the HRR peak and the belt burning rate of the conveyor. For scenario C is seen a higher HRR peak causing a high amount of smoke that cannot be kept away upwind from the fire.

For the determination of the belt conveyor belt fire classification model as well as its accuracy,

Table 4.12: Input parameters for scenario A and B.

Scenario	C	D
Air Velocity(m/s)	2.0	2.0
Tunnel Height(m)	2.6	2.0
Belt position(m)	1.0	1.0

Table 4.13: ANN-4 architecture and accuracy

Name	Architecture	C-V Accuracy (%)	Training Accuracy (%)	Test Accuracy (%)
ANN-4	Arch-3	96.01	96.30	95.0

the dataset was split into two. 90 percent which was used to select the architecture and train the ANN. The remaining 10 percent was used as testing data set. The Architectures shown in Table 4.9 were tested to select the best architecture for ANN-4 through 3-fold CV. Then, ANN-4 was trained using training dataset to determine the model and training accuracy. L2-norm regularization was also used during training of ANN-4. Finally, the model was tested using the test dataset with the objective of determining test accuracy of the model. A schematic showing a general view of the methodology for model determination is shown in Figure 4.17.

As indicated previously, air velocity, belt position and tunnel height parameters were used as input parameters for model determination. As shown in Table 4.13, training and test accuracies of 96.30% and 95.0% were obtained for ANN-4, respectively. This accuracy indicates the capability of the model of predicting 95 scenarios correctly out of 100 unseen scenarios. Following the same procedure for the determination of previous margin equations, points with estimate probabilities of 0.5 were obtained to determine the plane corresponding to the margin. Equation of the plane is shown in Equation 4.13. The R-squared of the plane equation was 1.0.

$$0.80V + 0.28BP - 0.35H = 1 \quad (4.13)$$

4.10 Conclusion

A model was developed to classify conveyor belt fires to determine the most adequate fire-fighting strategy. Additionally, the effects of design parameters such as belt position and mine entry dimensions on the fire classification were analyzed. This study was achieved using a methodology that consists of CFD simulations and ANNs. CFD simulations were used to predict the effects of fires spreading over conveyor belts. To predict realistic results, parameters used in CFD simulations were calibrated and CFD results were validated with experimental test results available in the literature. ANNs were used for the determination of parameters effects on fires outcome and the model for conveyor belt fire classification.

Validation and calibration results demonstrated that Yuan et al. [113] approach can predict real belt fire conditions with certain degree of certainty, despite the flame spread phenomenon is not solved completely due to the lack of physics in the model. In the model obtained using this approach, SBR was modeled as a single material component with reference rate and reference temperature of $0.0022(\text{s}^{-1})$ and 368°C , respectively. On the other hand, results of effects of design parameters on fire classification indicates that scenarios with closer belt positions to the roof and taller tunnel heights require a higher air velocity to be classified as Type I. Also, it was found that tunnel width has a negligible influence on the conditions at the attack position as well as on the fire classification. Besides, the critical velocity for mine conveyor belt fire scenarios simulated in this study was estimated between 1.7 m/s and 2.2 m/s. When air velocity, belt position, and tunnel height were used as input parameters, the conveyor belt fire classification model had accuracies of 96.30% and 95.00% for training and

testing dataset, respectively.

In addition to the determination of the design parameters effects on the fire classification, the margin classification model equation provides an approximation of the critical velocity for mine belt entries based on design parameters such as belt position and tunnel height. It can be said that methodology used in this study can be applied for fire classification on different mine fire locations contributing to better mine fire emergency plans. Future work should be focused on improving the modeling of ignition and pyrolysis processes of SBR as well as on formalizing the firefighters' exposure limits in underground mining. Also, future studies can address the determination of response time (i.e., approach time) that is defined as the time first responders and fire brigade members have to approach and start attacking the fire once the CO alarms are activated before at least one of the tenability limits is exceeded.

Chapter 5

Numerical and experimental study of foam in gob areas

5.1 Abstract

Fires in gob areas is a commonly reported event in U.S. underground coal mines and in countries worldwide. Foam application in real gob fires as well as previous experimental studies have demonstrated the capability of this technique to mitigate this type of fires. However, due to the complexity of modeling multiphase flow in porous media, there is no evidence of numerical models able to predict foam behavior through gob areas. Predictions of foam flow in these areas allow for determining optimal operational parameters during foam injection, and consequently improving the efficiency of this technique. For this reason, this paper presents an alternative approach to model foam as a non-Newtonian fluid through porous media. To test this approach, an experimental apparatus that consisted of a foam generator and a scaled down gob area was built. Results show proximity between numerical and experimental results, indicating that this approach could be an alternative for foam modeling through gob areas. Nevertheless, further experimental studies are required for complete acceptance of this approach.

5.2 Introduction

Fires in gob areas is a commonly reported event in U.S. underground coal mines as well as in countries worldwide. The main cause of this kind of fires is the spontaneous heating of coal [112]. This phenomenon occurs due to the low temperature reaction of coal leading to the generation of heat, when coal reacts with atmospheric oxygen. If the heat produced is not dissipated by conduction or convection, the coal temperature increases until its ignition temperature is reached. Coal oxidation rate is proportional to the temperature leading to a higher heat produced if there is no energy dissipation and consequently to fire occurrence. The high probability of fire occurrence in gob areas is due to the amount of coal left after mining and poor ventilation allowing for optimum conditions for spontaneous combustion. As fires in other mine locations, fire in gob areas represent a risk of an explosion in mines with appreciable levels of accumulated methane.

Different fire suppression technologies have been used to extinguish gob fires. It is noteworthy that gob fires are attacked remotely from the surface where fluids or gases are applied through boreholes. Different technologies such as water, grouting, spraying resistance agent, infusing gelatum, inert gases have been employed and applied. However, these technologies have not resulted effective due to drawbacks when applied to gob fires. Water and grouting have problem to extinguish fires in upper layers owing to the water capacity of flowing away due to the gravity [16]. The high cost of spraying resistance agents makes them prohibitive for this application as well as their limited range. The flow characteristics of gelatum are poor and its content of ammonium salt can produce a toxic gas such as ammonia. Inert gases are prone to diffuse through the gob area as well as the storage and gasification equipment of liquid nitrogen and carbon dioxide are complex and costly [2].

In recent years, foam technology has been developed gradually demonstrating to be an ef-

fective fire suppression technology. Foam has successfully controlled mine fires [94] showing capability of filling up mine entries and propagating upslope against ventilation pressure [77, 93]. In addition, foam has also been applied in open-pit mines extinguishing fires in caving zone [64]. The success of foam as mine suppression technology is attributed to three mechanisms, such as fuel isolation, fuel cooling, and oxygen dilution. Fuel isolation is generated because foam acts as barrier between the fuel and oxygen inhibiting the oxidation reaction. Fuel cooling occurs when heat is transferred from the fuel to foam because of the high specific heat of water. Due to the heat transfer, foam bubbles break down into foam solution that in contact with the fuel turns into water vapor. The release of water vapor around the fuel dilutes the oxygen concentration available for the combustion reaction [27]. In addition to these mechanisms, foam is able to accumulate and attach to hydrophobic surfaces such as coal due to surfactants in foam concentrate [67].

Previous experimental studies have been carried out to study the foam behavior [22, 64]. However, there is no evidence of numerical models able to simulate foam through gob areas. For this reason, the objective of this study was to test a simpler approach to simulate foam as a non-Newtonian fluid through gob areas. The approach was tested using experimental data obtained from a properly scaled gob area experimental setup. The model was developed in the commercial software Ansys Fluent. It is noteworthy that a better understanding of foam behavior when applied through gob areas allows for predicting foam flow behavior, such as spread, velocity, and accumulation. In the same way, it allows for determining optimal operational parameters during foam injection, such as application foam characteristics (density, expansion ratio, and viscosity), application velocity, and pressure, as well as physical parameters, such as borehole diameter and location.

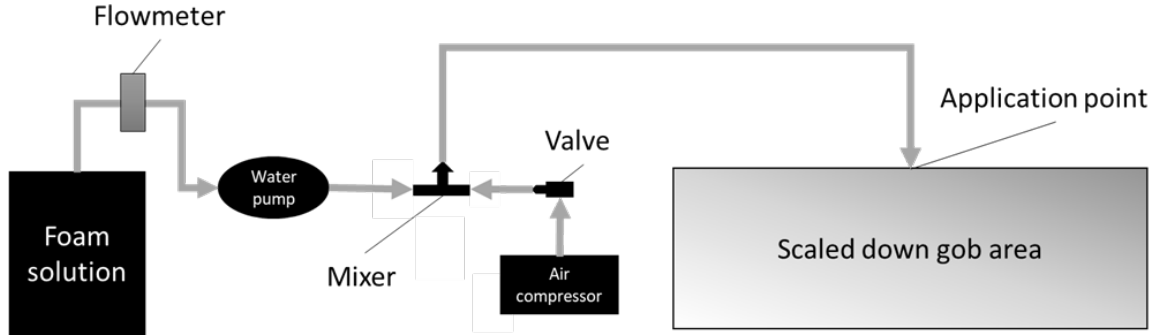


Figure 5.1: Experimental setup

5.2.1 Methodology

The experimental setup consisted of a foam generator and a scaled down gob area as shown in Figure 5.1. The apparatus dimensions and operational experimental parameters were obtained applying the Buckingham Pi theorem and the concept of similarity. The numerical model was built in the commercial software Ansys Fluent. The geometry in the numerical model and modeling parameters were set to replicate the experimental conditions as much as possible. Details about the scaling methodology and results, experimental setup, and numerical model design consideration are detailed in the following subsections.

Experimental setup scaling

It is important to mention that we are interested in the flow of foam through the gob area, which is a large system where experimental studies are hard to perform due to difficult access, cost, and control of parameters involved. Thus, collection of experimental results for the approach testing were collected from a scaled down apparatus.

The Buckingham Pi theorem along with the concept of similarity were used to scale down the gob area experimental setup [9]. This method also known as dimensional analysis has been widely used for scaling process of flow through porous media in reservoir engineering.

The Buckingham's Pi theorem states that for every single system described by N variables and parameters in M fundamental dimensions, there are $N-M$ independent dimensionless Pi parameters that must be kept invariant during scaling to maintain similitude. These dimensionless Pi parameters characterize the dynamics of the system [9, 76]. Thus, if the dimensionless Pi parameters are equal for both systems—as shown in Equation 5.1 and they maintain geometrical similarity, both systems behave similarly and are physically similar. Geometrical similarity is maintained when the scale factor defined in Equation 5.2 is constant for both system dimensions where a scale factor equal to $1/a$ refers to a down geometric scaling by the quantity a . If both systems maintain geometrical similarity, the dimensionless Pi numbers can be used as scaling laws in which any knowledge observed from one system provides knowledge about the other.

$$\pi_1 = \pi'_1, \quad \pi_2 = \pi'_2, \quad \pi_3 = \pi'_3 \quad \pi_n = \pi'_n \quad (5.1)$$

$$K = \frac{x'}{x} = \frac{1}{a} \quad (5.2)$$

Where, π is a Pi number, K is the scale factor, x is a system dimension, and the prime refers to the scaled down system.

The methodology used to find the scaling laws for the gob area was based on Greenkorn [36]. In Greenkorn's study, the author(s) derived the scaling laws for oil reservoirs. The first step of the methodology used was focused on defining the variables involved in foam flow through porous media. These variables are shown in the following Equation.

$$G(H, W, t, V, k, \rho, D, \mu, \delta, P) = 0 \quad (5.3)$$

Where H and W are the height and width of porous media, respectively. t is the time, V is the foam application velocity, k is the permeability of the porous media, ρ is the fluid density, D is the fluid dispersion, δ is the diameter of the application point, and P is foam application pressure.

Assuming that the porosity of the experimental setup and gob area are the same and foam is applied in both systems, the Pi numbers that result from the dimensional analysis are shown in Equation 5.4.

$$G\left(\frac{H}{W}, \frac{tv}{W}, \frac{k\rho g}{\mu V}, \frac{kP}{\mu, WV}, \frac{D}{WV}\right) = 0 \quad (5.4)$$

Then, the principle of corresponding states as shown in Equation 1 is applied. The equations obtained that allow for determining the geometric and operational parameters of the scaled down system are as follows:

$$H' = \frac{H}{a} \quad (5.5)$$

$$W' = \frac{W}{a} \quad (5.6)$$

$$V' = \frac{V}{a} \quad (5.7)$$

$$\delta' = \frac{\delta}{a} \quad (5.8)$$

$$k' = k * a \quad (5.9)$$

$$t' = \frac{t}{a^2} \quad (5.10)$$

$$P' = \frac{P}{a} \quad (5.11)$$

Table 5.1 shows the geometric and operational parameters of the gob area portion. The height of the gob area portion was determined based on the gob area dimensions of a partner underground coal mine. The width and length of the gob area portion were determined based on the laboratory space and availability of materials. The dimensions along with the operational parameters calculated using Equations 5.5-5.11 and used in the experimental setup are also shown in Table 5.1. It is important to mention that the large system was scaled down by 10 ($a = 10$). Foam application velocity (V) is reported as a range, since this parameter was varied for testing the approach. The Foam application velocity range was determined based on the capacity of different foam generators previously used in real gob areas [14, 77, 93]. Additionally, it is noteworthy that the time was scaled down by 100 ($a^2 = 100$) and a homogeneous permeability in the gob area was used. The time values shown in Table 5.1 indicate that 1 minute of foam flowing through the experimental gob area is equivalent to 1.66 hours in the gob area portion.

Table 5.1: Geometric and operational parameters of the experimental setup and the scaled down gob area portion

Parameter	Gob area portion	Experimental setup
Height (H) (m)	3	0.3
Width (W) (m)	7.5	0.75
Length (L) (m)	3	0.3
Diameter(δ) (m)	0.7	0.07
Velocity (V) (m/s)	10-80	1-8
Time	1.66 hr	1 min

5.3 Experimental apparatus

Figure 5.1 illustrates the experimental setup which consists of a foam generator and the experimental gob area. The surfactant solution was pushed by a variable speed water pump to go to an in-line mixer. Foam is produced when compressed air is mixed with the surfactant solution in the mixer. A flowmeter was used to determine and control the flowrate solution and a valve was used to control the air flowrate and pressure. Foam flow rate, expansion ratio, and density were determined by measuring the foam volume produced, solution flowrate, and time. Expansion ratios calculated using Equation 19 lower than 4 were generated in this study. Foam was characterized by a homogeneous distribution of bubble sizes with a texture similar to shaving cream. The foam concentrate used in the experiment was Chemguard X-tra, which was diluted with water to a 1 percent solution by volume. Thus, foam solution was a mixture of 1-part liquid foam concentrate and 99 percent parts of water. The diameter of the hose connected to the mixer was 0.007 m based on the scaling-down results.

The experimental gob area was set up in a rectangular glass container with dimensions shown in Table 5.1. The top side of container was open, and the bottom side was perforated with holes for foam drainage. In the experimental gob area, two different parameters were measured: the foam spread (FS) at the bottom of the container as shown in Figure 5.2,

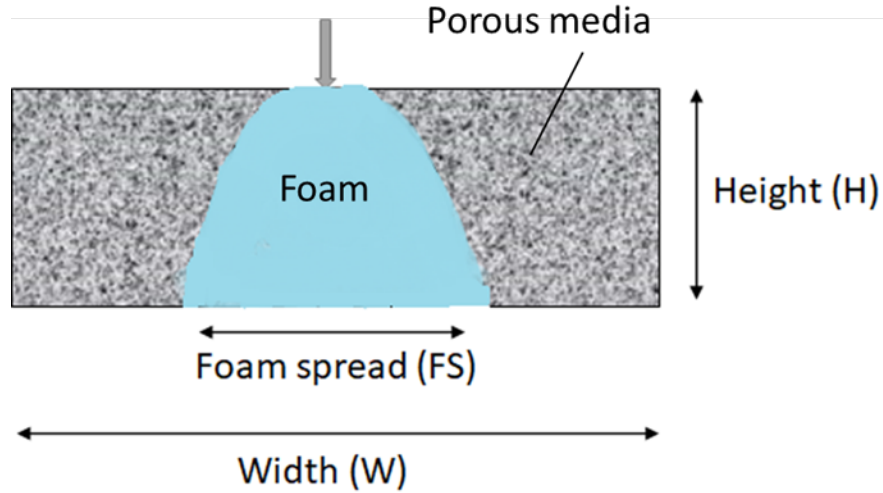


Figure 5.2: Experimental setup

and the time taken by the foam to go through the height of the porous media (T). Both parameters were measured using a video camera installed in front of the experimental gob area.

5.4 Numerical model

As previously mentioned, numerical simulations of foam through porous media were carried out in Ansys Fluent [4]. In this CFD software, it can be defined a cell zone in which the porous media model is applied, and the pressure loss is determined. The porous media model is the governing momentum equations with an added momentum sink as shown in Equation 5.12. The momentum sink for a simple homogeneous porous media defined in Equation 5.13 contributes to the pressure gradient in the porous cell, generating a pressure drop that is proportional to the fluid velocity in the cell. The momentum sink equation is also known as Ergun equation. The first term on the right of the Ergun equation is the Darcy law equation and the second term is the Forchheimer equation. The momentum equation can be

compressed as shown in Equation 5.14 [4]. Thus, Ansys fluent only require two parameters to characterize the porous media such as viscous resistance (D) and inertial resistance (F). The values for these two parameters were found through model calibration with experimental results.

$$\frac{\delta(\rho\vec{v})}{\delta t} + \Delta(\rho\vec{v}\vec{v}) = -\Delta p + \nabla \cdot (\tau) + \rho g + S_i \quad (5.12)$$

In the above Equation, ρ is the fluid density, $\vec{v}$ is the velocity vector, t is the time, p is the static pressure, τ is the stress tensor, and $\vec{g}$ is the gravitational force.

$$S_i = - \left(\frac{\mu}{\alpha} v_i + C_2 \frac{1}{2} \rho |v| |v_i| \right) \quad (5.13)$$

Where, α is the permeability, μ is the viscosity, and C_2 is the inertial resistance factor

$$S_i = -(D\mu v_i + F\rho |v| |v_i|) \quad (5.14)$$

The 2D CFD domain used to perform the numerical simulations is shown in Figure 5.3. The same dimensions of the experimental gob area and operational parameters shown in Table 5.1 were used in the simulations. The domain was divided into two different zones: the well zone and porous media zone as shown in Figure 5.3. Viscous resistance (D) and inertial resistance (F) were set to the porous media zone. The k - ω viscous model shown in Equations 5.15 and 5.16 to model turbulence and solve for turbulence kinetic energy (k), and the specific dissipation rate (ω) were used. In addition, the volume of fluid (VOF) model was used to simulate foam and air flow through the porous media.

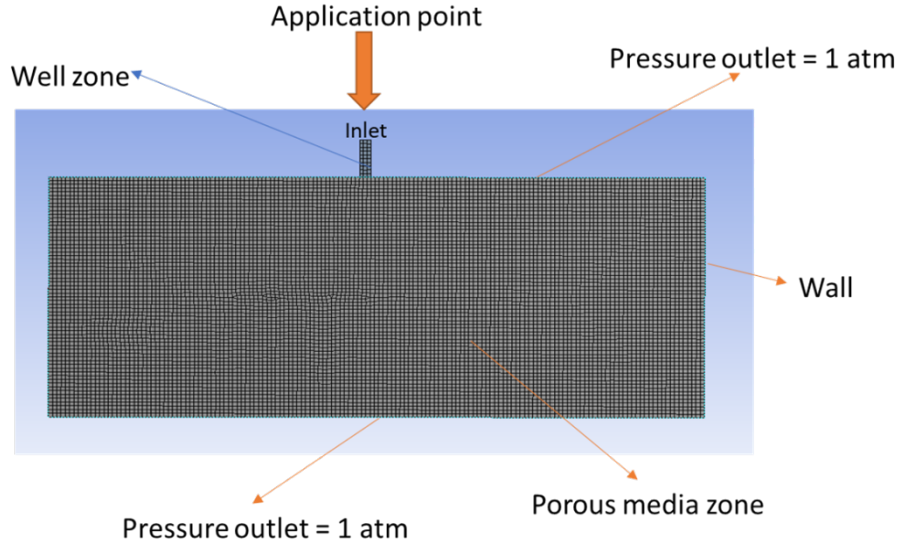


Figure 5.3: CFD domain and boundary conditions

$$\frac{\delta}{\delta t}(\rho k) + \frac{\delta}{\delta x_i}(\rho k u_i) = \frac{\delta}{\delta x_j} \left(\Gamma_k \frac{\delta k}{\delta x_j} + G_k - Y_k + S_k \right) \quad (5.15)$$

$$\frac{\delta(\rho \omega)}{\delta t} + \frac{\delta}{\delta x_i}(\rho \omega u_i) = \frac{\delta}{\delta x_j} \left(\Gamma_\omega \frac{\delta \omega}{\delta x_j} + G_\omega - Y_\omega + S_\omega \right) \quad (5.16)$$

In these equations, G_k represents the generation of turbulence kinetic energy due to mean velocity gradients. G_ω represents the generation of ω . Γ_k and Γ_ω represent the effective diffusivity of k and ω , respectively. Y_k and Y_ω represent the dissipation of k and ω due to turbulence. S_K and S_w are user-defined source terms.

The VOF model can model immiscible fluids by solving a single set of momentum equations and tracking the volume fraction of each fluid phases throughout the domain [4]. This model can track the interface between the phases solving the continuity equation for the volume fraction of the phases. For the q^{th} phase, this equation can be expressed as follows:

$$\frac{1}{\rho q} \left[\frac{\delta}{\delta t} (\alpha_q \rho_q) + \Delta \cdot (\alpha_q \rho_q \vec{v}_q = S_{\alpha q} + \sum_{P=1}^n (\dot{m}_{pq} - \dot{m}_{qp}) \right] \quad (5.17)$$

Where $\dot{m}_{qp}$ is the mass transfer from phase q to phase p and $\dot{m}_{pq}$ is the mass transfer from phase p to phase q .

It is noteworthy that Equation 5.17 is solved for the secondary phase. Thus, the volume fraction for the primary phase will be computed based on the following constraint:

$$\sum_{q=1}^n \alpha_q = 1 \quad (5.18)$$

Atmospheric pressure on the top of the porous media was set and the foam application velocity was set at the top of the well zone as shown in Figure 5.3. A surface tension of 0.072 N/m between the foam and air was used.

5.4.1 Rheological parameters

Previous studies of rheology of firefighting foams have demonstrated that this type of foam behaves as shear thinning fluids represented by the power law model shown in Equation 5.19 [5, 32, 104, 105, 106]. In other words, foam viscosity is proven to be inversely proportional to the shear rate. Rheological parameters used for the numerical simulations are shown in Table 5.2. These values were obtained of a rheological study performed by Gardiner et al. [32] to foam with same expansion ratios used in this study.

$$\mu = nk\gamma_w^{n-1} \quad (5.19)$$

Where μ is the foam viscosity [Pa-s], γ_w is the wall shear rate (s^{-1}), k is the consistency

Table 5.2: Foam rheological parameters used for the numerical simulations [32]

$k(Pa - s^n)$	n	Min viscosity($Pa - s$)	Max viscosity($Pa - s$)
2.63	0.29	0.02	0.5

Table 5.3: Grid information

Grid level	Nx	Ny	Nt	GCI
Coarse	40	100	4,000	0.063
Medium	60	150	9,000	0.006
Fine	120	300	36,000	0.005

index ($Pa - s^n$), and n is the power law index.

5.5 Grid independence study

A grid sensitivity analysis was performed using three different grid sizes. The foam spread at the bottom of the experimental gob areas was chosen for this analysis. The coarse, medium, and fine grid levels were composed of 900, 4500, and 9,000 quadrilaterals, respectively. Grid information is shown in Table 5.3, in which Nx and Ny refers to the grid number along the X and Y axis, respectively; and Nt refers to the total number of quadrilaterals. The foam spread for different foam application velocities obtained by the grid levels are compared in Figure 5.4. Foam spread difference between the medium and fine grid size is lower than 2 percent. In addition, the grid convergence index (GCI) suggested by Roache [84] was calculated for each grid size. The fine grid size was used to ensure the accuracy of the numerical simulation results.

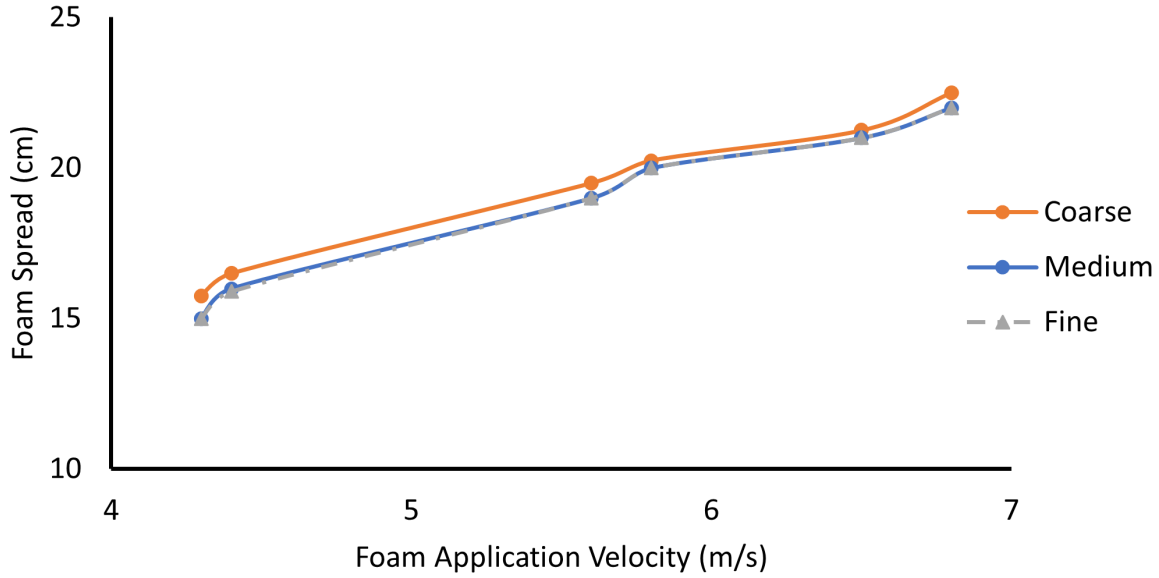


Figure 5.4: Results of grid sensitivity analysis

5.6 Results and discussion

5.6.1 Hypothesis testing

Multiple foam flowrates were obtained from different foam solution and air flowrates during foam generation process. However, the only foam flowrates applied to the gob areas were the ones in which foam was stable. It was noticed that for most of the air and foam solution rate combinations, the foam was not homogeneous and mainly composed of foam solution. Table 5.4 shows the foam and solution flowrates as well as foam velocity in which stable foam was generated. In addition, expansion ratio calculated using Equation 5.20 is also shown in Table 5.4. It is noteworthy that foam was stable for a narrow foam solution flowrate range between $6.96\text{E-}05 \text{ m}^3/\text{s}$ and $7.65\text{E-}05 \text{ m}^3/\text{s}$, and a velocity range between 4.3 m/s and 6.8 m/s . The generation of stable foam at higher flowrates was limited to the air flowrates delivered by the air compressor. They were not high enough to generate stable foam for foam

Table 5.4: Geometric and operational parameters of the experimental setup and the scaled down gob area portion

Test	$Q_{foam} (m^3/s)$	$Q_{sln} (m^3/s)$	Foam velocity (m/s)	Expansion ratio (E)
1	0.00016	$6.96 \times 10_5$	4.3	2.3
2	0.00017	$7.08 \times 10_5$	4.4	2.4
3	0.00022	$7.10 \times 10_5$	5.6	3.1
4	0.00022	$7.10 \times 10_5$	5.8	3.1
5	0.00025	$1.09 \times 10_4$	6.5	2.3
6	0.00026	$7.65 \times 10_5$	6.8	3.4

solution flowrates greater than the ones shown in Table 4. It is also worth of mentioning that the proposed modeling approach was tested using homogeneous permeability. Thus, the gob area in the experimental tests and numerical simulations does not represent fully the complexity of a gob area. As previously mentioned, this study is a first step for introducing a simpler modeling foam approach in porous media.

$$E = \frac{Q_{foam}}{Q_{sln}} \quad (5.20)$$

Numerical and experimental results of foam spread (FS) and time of foam flowing through the porous media (T) for different foam velocities are shown in Figures 5.4 and 5.5. The error percent for numerical results of foam spread and foam flow time were calculated as follows:

$$E_{FS} = \frac{FS_{Num} - FS_{Exp}}{FS_{Exp}} \quad (5.21)$$

Where, E_{FS} is the percent error for foam spread, FS_{Num} is the foam spread predicted by the numerical model, FS_{Exp} is the foam spread measured in the experimental test.

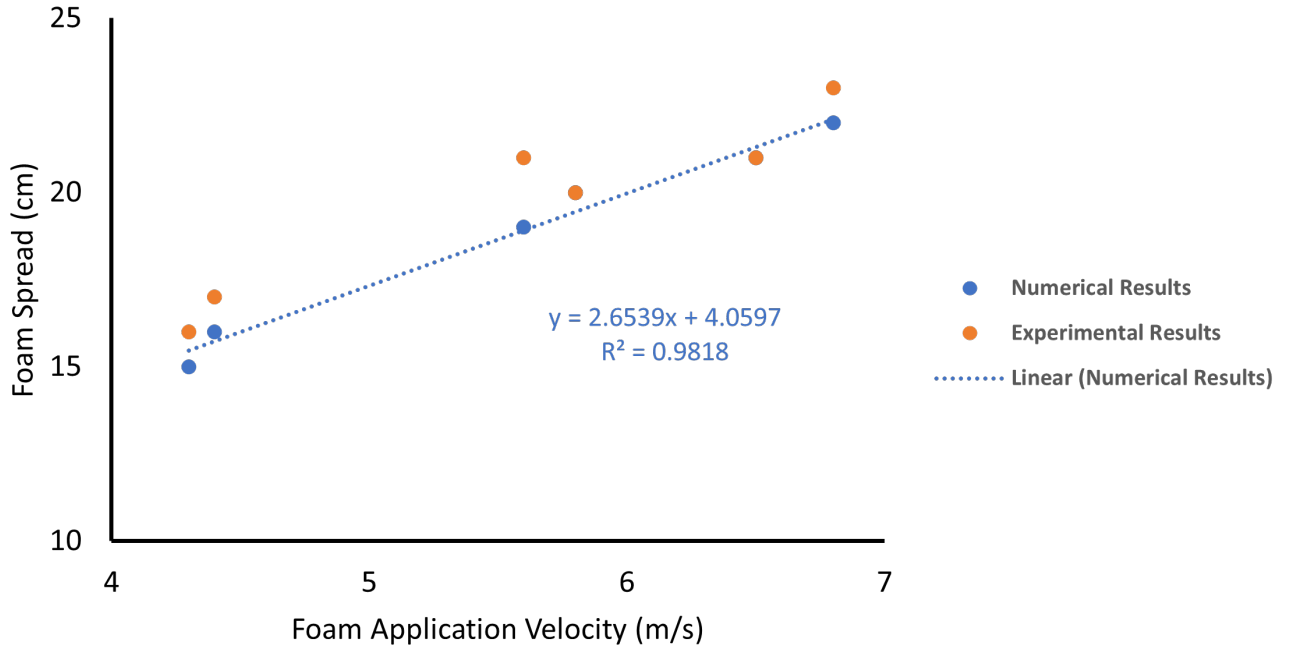


Figure 5.5: Foam spread (FS) results

$$E_T = \frac{T_{Num} - T_{Exp}}{T_{Exp}} \quad (5.22)$$

Where, E_T is the percent error for time of foam flowing through the porous media, T_{Num} is the time predicted by the numerical model, T_{Exp} is the time measured in the experimental test.

Table 5.5 shows the percent errors for foam spread and time for each foam velocity. In addition, Table 5.5 shows the error percent mean and standard deviation for foam spread (FS) and time of foam flowing through the porous media (T). Values shown in Table 5.5 indicates that numerical and experimental results are in a good agreement demonstrating the potential of the hypothesis tested to be applicable in modeling of low expansion foam through gob areas. Additional testing is required in which the accurate foam rheological parameters are used, and wider range of foam application velocity and expansion ratios

Table 5.5: Percent errors for FS and T

Test	E_{FS} %	E_T %
1	6.3	0.7
2	11.1	1.3
3	9.5	3.7
4	0.0	4.3
5	5.0	3.8
6	4.3	0.9
$\mu \pm 2\sigma$	6.0 ± 3.6	2.4 ± 1.5

are tested. It is necessary to determine what is the maximum expansion ration which the proposed approach is accepted.

5.7 Conclusions

An alternative approach to simulating low expansion firefighting foam through mine gob areas as a non-Newtonian fluid was tested, using experimental results. Experimental results were obtained from a scaled down setup based on regular dimensions of mine gob areas and foam application operational parameters in the U.S. This guaranteed retaining the physics of this process, allowing for a precise evaluation of the new simulation approach. The scaling analysis was performed applying the Buckingham Pi theorem and the concept of similarity, leading to the determination of scaling laws. Foam spread and foam flowing time through the gob area were predicted using the numerical model and measured in the experimental setup for different foam application velocities. Then, they were compared calculating the error percent. Results show that the mean and standard deviation of error percent for foam spread were 6.0 and 3.6, respectively. Additionally, the mean and standard deviation of error percent for foam flowing time through the gob area were 2.4 and 1.5, respectively. These low error values demonstrate the proposed approach could be an alternative to simulate foam

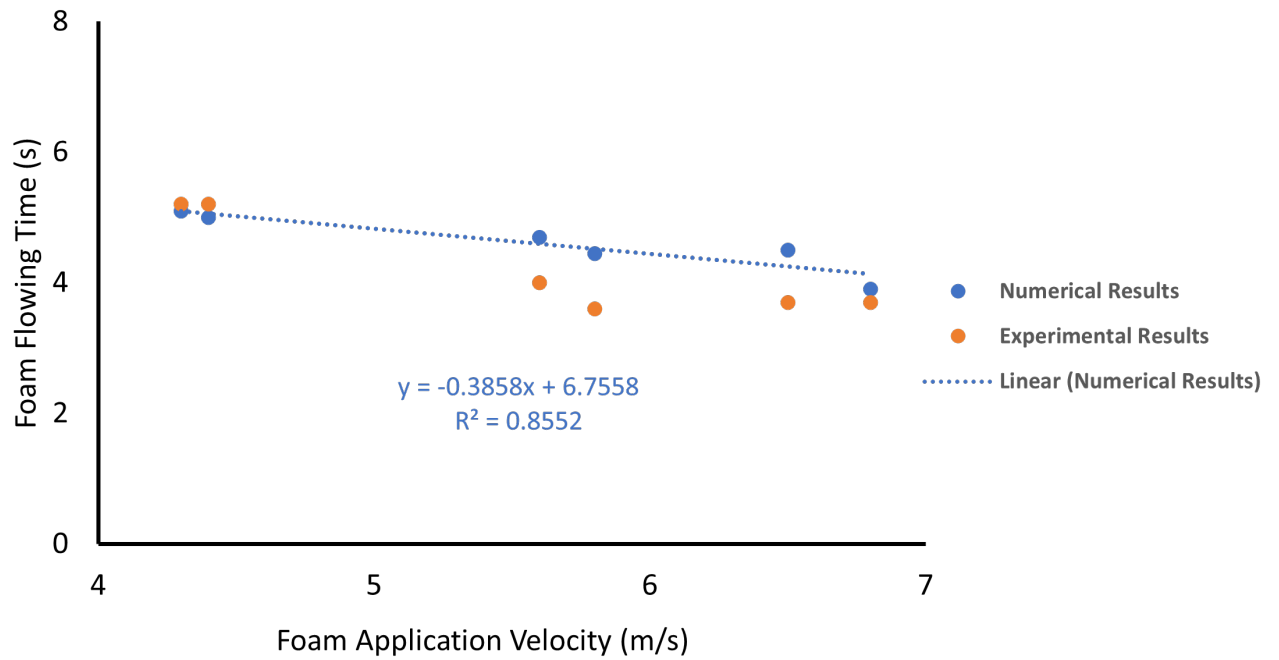


Figure 5.6: Time of foam flowing through the porous media

under the foam characteristics and operational parameters used in this study. However, for complete acceptance of this approach, it is recommended to test wider range of foam application velocity and expansion ratios in future work. In addition, the use of a wider range of foam expansion ratios could be useful for the determination of maximum expansion ratio for which this approach is applicable.

Chapter 6

Conclusions and future work

6.1 Summary and conclusions

This research focuses on advancing the state-of-the-art in mine fire characterization and mine fire emergency response plans in underground coal mines. In the first part of this research, a data-driven approach to classify fires to recommend the most suitable decision to the mine firefighting personnel was developed. A feed-forward ANN was trained to classify fires using measurable and available data during ongoing mine fires as input parameters (CO concentration, air velocity, time, and mine entry dimensions). The data for training and testing the network was generated from the analysis of 500 CFD and FSSIM simulations. The overall accuracy and weighted average F1-score of the ANN was 96% for training and testing dataset. Results also show that 95% of ANN predictions of fire class change should not have a time greater than 18 s of the true fire class change for any fire position in the tunnel. These values demonstrate the capability of the model to classify fires with high a degree of precision, despite the limited information available during ongoing mine fires. However, much of the classification error can be attributed to the performance of the ANN classifying fire Class II and III. This poor performance was identified resulting from two primary sources. The first source was related to the evolution of the conditions at the attack position, which is not immediately reflected in the variation of the CO concentration downwind from the fire. Higher air velocities make the combustion products travel faster downwind from the fire.

Nonetheless, lower air velocities reduce the travel time of combustion products, causing the ANN to misclassify fires. The second error source was related to the small number of samples of class II and III due to the quick evolution of the mine atmospheric conditions and the short time in which scenarios are classified as Class III. Finally, the impact of fuel variation on the data-driven approach performance was determined and three recommendations were proposed to deal with the fuel uncertainty.

In the second part of this research, a data-driven approach to predict response time for firefighters and fire size based on available and measurable input parameters during ongoing mine fires was presented. The data-driven approach was composed of two interconnected feedforward ANNs. In these, the predictions of the fire size by the first ANN were used by the second ANN to predict the response time. The input parameters for the data-driven model were CO concentration, air velocity, time, and mine entry dimensions. The data for training and testing the ANNs was collected from 300 scenarios simulated in a CFD model for the determination of the conditions at an attack position 5.0 m upwind from the fire and a network model to calculate the CO concentration downwind from the fire. Results of the performance of the ANN-1 and entire model when testing dataset was used indicated that 95% of fire size and response time predictions should be within ± 64 kW and ± 32 s of the true values obtained in the fire models, respectively. The major error source was identified to be in the predictions of fire size by ANN-1. The information provided by the input parameters is insufficient to have lower error predictions. However, it should be considered that the input parameters are the ones available and measurable during underground coal mine fires. Furthermore, the degree of accuracy of the models met the desired performance and is considered precise enough to contribute with the decision-making process of the firefighting personnel.

In the third part of this research, a conveyor belt fire classification was developed to determine

the most convenient decision during conveyor belt fires. In addition, the effects of design parameters and air velocity on fire class were analyzed. This study was achieved using a methodology that consists of CFD simulations and ANNs. CFD simulations were used to predict the effects of fires spreading over a conveyor belt. To predict realistic results, parameters used in the CFD model were calibrated with experimental test results available in the literature. ANNs were used to determine the parameter effects on fires outcome and the conveyor belt fire classification. Results indicated that a SBR conveyor belt fire can be modeled as a single material component with reference rate and reference temperature of 0.0022 s^{-1} and $368 \text{ }^{\circ}\text{C}$ following Yuan's approach [113]. The HRR peak predicted from the CFD model and obtained in the experiment showed good agreement. Regarding the effects of design parameters and air velocity, results indicated that scenarios with closer belt positions to the roof and taller tunnel heights require a higher air velocity to be classified as Type II. It was also found that tunnel width has a negligible influence on the fire classification. Additionally, critical velocity for a mine conveyor belt fire was estimated between 1.7 m/s and 2.2 m/s . The conveyor belt fire classification model had accuracies of 97.44% and 95.00% for training and testing dataset, respectively.

Chapters 2-4 represents a significant advancement in mine fire characterization and mine fire emergency response plans in underground coal mines. Prior to the framework presented here, there is no evidence of tools that based on available information during ongoing underground coal mine fires can recommend actions to the firefighting personnel, and predict fire size and response times. Using the tools presented in this work make this possible. These models also contribute to the compliance of the mining regulation which requires that each operator of an underground coal mine has an emergency and firefighting program that instructs all miners in the procedure that they must follow if a fire occurs (Title 30 CFR § 75.1502b). Most mine fire scenarios are unique and a generalized procedure is not applicable for all

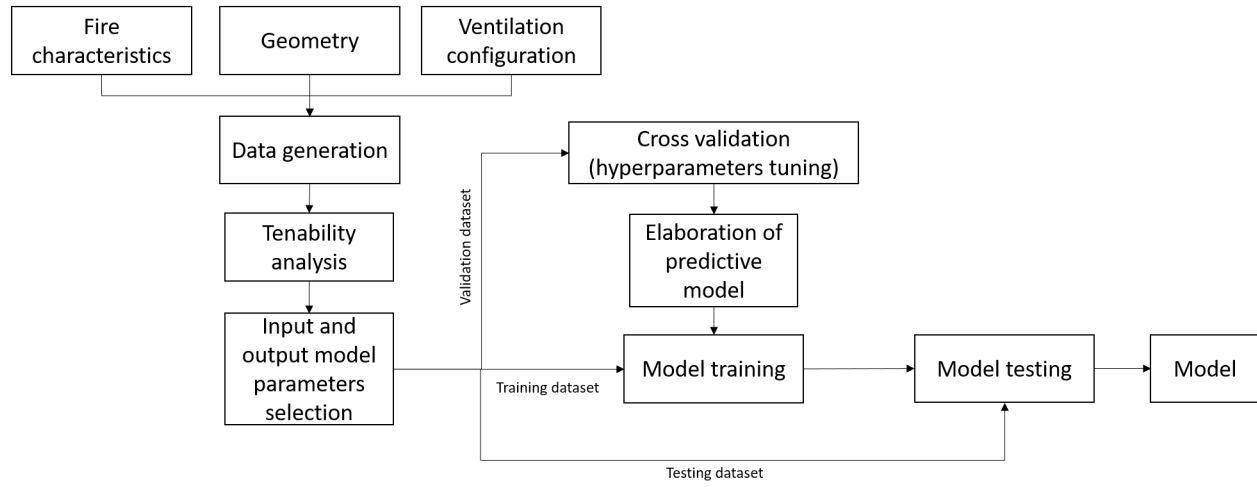


Figure 6.1: Flowchart for elaboration of data-driven approaches as the proposed in Chapters 2 and 3

situations. However, the implementation of the models proposed and elaborated herein will comply with this regulation as to have a specific procedure for each possible fire scenario. In addition, these data-driven approaches also can be used for training and preparing the firefighting personnel prior to fire occurrence. They can be used as a tool to reproduce multiple fire scenarios outcomes allowing for adequate hands-on training which would build confidence and skill levels on firefighters, as well as show them what to expect in the event of a fire. Thus, firefighters could have a better understanding of the relationship between fire conditions, deployment time, and firefighting decision. Figure 6.1 shows a flowchart that may be followed for development of data-driven models as the proposed in this study. It is noteworthy that the the data-driven approaches are site-specific, which means that they can be used only in similar geometries of fire scenarios utilized for training.

In the fourth part of this research, an alternative approach to simulating low expansion firefighting foam through mine gob areas as a non-Newtonian fluid was tested, using experimental results. Experimental results were obtained from a scaled down setup based on regular dimensions of mine gob areas and foam application operational parameters in

the U.S. Foam spread and foam flowing time through the gob area were predicted using the numerical model and measured in the experimental setup for different foam application velocities. Results demonstrate that this approach can be an alternative to simulate foam under the foam characteristics and operational parameters used in this study. It is important to mention that there is little guidance for foam injection into gob areas. Normally, coal mining operators apply firefighting foam without the knowledge of the optimal operational parameters. The knowledge of optimal operational parameters (associated to foam characteristics and foam application) will increase the probability to reach and extinguish the fire. Foam modeling is the best path for the determination of the relationship between operational parameters and foam behavior through the gob area (foam spread, dispersion, accumulation, and propagation). Thus, this study is a first step for designing standard guidelines for foam injection into gob areas. In addition, foam modeling could contribute to the development of new firefighting foams that meet with the desired foam characteristics to increase the probability of gob fire extinguishing. However, for complete acceptance of this approach, wider range of foam application velocity and expansion ratios in heterogeneous permeability porous media should be tested in future work.

In the appendix of this dissertation, the current state-of-the-art in gas sensing in underground coal mines was detailed and optical fiber sensing was described. Furthermore, the applicability of optical fiber sensing technology for continuous and distributed sensing of gases at the longwall face was presented along with preliminary design for a full-face sensor. Limitations of gas sensors currently used in underground coal mines were discovered. Within these limitations, it was found that catalytic sensors have some operational problems when the minimum oxygen concentration is lower than 12 percent in the air, the methane concentration does not fall between the range of 0 to 5 percent, or other gases such as ethane, propane, or flammable gases are present in the atmosphere. FOS were found as

an alternative due to their intrinsic safety, electrical passivity, and deployability in remote, isolated, hazardous, and limited spaces. Finally, the fundamental concepts and preliminary design of a new platform of fiber distributed gas sensing called PoroSense were outlined. It is noteworthy that this proposed platform could improve the input data collection for the data driven approaches presented in this research.

Overall, this dissertation focuses on advancing the state-of-the-art in mine fire characterization and mine fire emergency response plans in underground coal mines. During the elaboration of data-driven approaches, the review of the current state-of-the-art in mine sensing, the proposal of locations for a new technology for coal mine sensing, and the hypothesis testing of simulating foam through gob areas as a single phase non-Newtonian fluid, the following conclusions have been identified:

- Data-driven models can predict mine fire conditions and perform analysis on them to classify fires based on the most suitable decision for firefighters. Despite the information in underground coal mines being limited, these models can show good classification performance using only input parameters available during mine fire emergencies.
- Data-driven models can be composed of ANNs to simultaneously predict parameters related to fire characteristics such as fire size, mine fire conditions for firefighters, and response time. All these parameters can be predicted in real time during ongoing mine fire scenarios using only information available and measurable.
- Data-driven models can contribute to the compliance of mining regulation of instructing all miners in the procedure that they must follow if a fire occurs. In addition, these models also can be used for training and preparing the firefighting personnel prior to fire occurrence.
- Estimation of the atmospheric conditions during mine conveyor belt fires can be carried

out based on design parameters such as mine entry dimensions and belt position, as well as air velocity. Furthermore, belt fires can be classified based on the recommended decision to firefighters using these parameters as inputs to the model.

- It is possible to perform mine fire characterization and fire risk analysis in real time with the information available in underground coal mines, allowing for less subjective decisions during mine emergency scenarios.
- Preliminary numerical and experimental results demonstrate that foam flow through porous media could be modeled as a single phase non-Newtonian fluid. However, additional experimental testing is required for the complete acceptance of this hypothesis.
- A new platform of fiber distributed gas sensing, such as PoroSense, could improve the input parameters collection for the data driven approaches presented in this research and overcome the limitations of the current sensors used in underground coal mines.

6.2 Future work

This majority of this work (Chapters 2,3,4) represents a first step in creating data-driven approaches for mine fire characterization and mine fire emergency response plans in underground coal mines. The continuity of this work has the potential to transform the field of fire risk, hazard analysis, preparedness, and emergency response in underground coal mines or other scenarios where enclosed fires can occur.

Results presented in this dissertation show the capability of driven approaches to predict mine fire conditions, response time and parameters, as well as the capability to classify fires using only measurable and available data during ongoing mine fires. However, before completely implementing these data-driven approaches on real fire scenarios, it is necessary

to use more detailed CFD fire setups, which provide broader and more realistic input to emergency situations. As discussed in Chapter 4, future work should focus on improving the modeling of ignition and pyrolysis processes of SBR. If possible, it is also recommended to incorporate experimental data into the training process that could allow for more precise predictions of the data driven approaches proposed in Chapters 2, 3, 4. The impact of fuel variation on a data-driven approach was determined and some recommendations to deal with fuel uncertainty were proposed, but a further evaluation is needed. Such an evaluation should be performed to determine the scenarios where each recommendation can be applied. Additionally, it would be interesting to test the applicability of data-driven approaches as the ones elaborated in this study in more complex mine geometries. In addition, incorporating a recurrent layer to the ANN architecture of Chapter 3 could lead to more accurate prediction performance of fire size and response time.

Chapter 5 focused on predicting foam spread and foam flowing time through the gob area in the numerical model and collected in an experimental set up for different foam application velocities. Results show proximity between numerical and experimental results, indicating that this approach could be an alternative for foam modeling through gob areas. However, future work is recommended to test wider range of foam application velocity and expansion ratios in a heterogeneous permeability porous media which fully represents the complexity of a gob area for complete acceptance of this approach. In addition, the use of a wider range of foam expansion ratios could be useful for the determination of the maximum expansion ratio for which this approach is applicable. In future studies, a more precise control of the airflow used to generate foam is also recommended as better air control allows for stable foam in wider range of velocity and expansion ratios.

In Appendix A, a new technology of gas sensing in underground coal mines called PoroSense is presented. PoroSense is a porous-clad optical fiber that would allow for an intrinsically

safe, electrically passive, and deployable in remote, isolated, and hazardous spaces technology. In addition, this technology allows for continuous and distributed sensing, leading to a more precise information collection during mine fire events. Continuous and distributed sensing could result in better predictions by the developed data-driven approaches. Modeling of normal ventilation conditions and fire conditions would allow for more robust recommendations on sensor locations.

Ultimately, this work contributes to better mine fire response, predictions of mine fire conditions, and can be used to train responders generally, and in site specific approaches.

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Appendices

Appendix A

Applicability of distributed optical fiber sensing for a longwall face

A.1 Abstract

Real-time sensing of mine gases is critical to safety in underground coal mines, as changes in the atmosphere can occur quickly and lead to explosive environments. Over the last century of sensing development for underground coal the persistent challenges in sensor design are ruggedability and permissibility for underground coal mines, especially given US regulation. In particular, longwall gob represents a highly dynamic and high risk area which is difficult to access and characterize in real time. This paper details the current state-of-the-art in gas sensing in underground coal mines, and describes optical fiber sensing. Additionally, the applicability of optical fiber sensing technology for continuous and distributed sensing of gases at the longwall face, is presented, along with preliminary design for a full face sensor. It is noteworthy that the application of this new technology could contribute with the data collection for the elaboration of data driven approaches proposed in previous chapters.

A.2 Introduction

Longwall mining is a technique in which large amounts of flammable and toxic gases such as methane are released during and after the coal extraction [10, 13, 95]. Methane is a combustible gas that when its concentration in a mixture with air is between 5% to 15%, it becomes explosive. It has been demonstrated that the most dangerous scenario takes place when the concentration of methane in air is 9.5 percent, since at this concentration the mixture reaches the perfect oxidation point (complete combustion of the air-methane mixture). Methane emissions are primarily produced at the longwall face and gob areas. When coal is longwall mined a considerable amount of methane is released at the face. If the methane concentration is within the explosive zone, an explosion can occur causing catastrophic consequences. On the other hand, gob areas are formed when coal has been mined out and the space generated is filled up with roof rock strata that has collapsed. The gob area is usually composed of unmined coal and strata that along with overlying coal beds can keep releasing methane after the panel extraction is carried out. Oxygen levels can decrease in this zone due to coal oxidation, allowing for the increase of remaining gases such as methane and carbon dioxide. This acts to create a lower risk of explosion, given that the explosive range of methane is 5 to 15 percent (by volume) in the presence of at least 12 percent oxygen. However, atmospheric changes, particularly the influx of fresh ventilation air to the gob can quickly create an explosive environment [10]. In the United States mines, explosions related to methane accumulation at the working face and gob areas have caused numerous fatalities and mine closures. The most well-known recent gob area explosion is the Upper Big Branch explosion in 2010, with 29 fatalities. Other recent mining incidents related to working face and gob explosions are: Willow Creek mine explosion with 2 fatalities in 2000, and Sago mine explosion with 12 fatalities in 2006 [13].

Due to the facts mentioned previously, real-time sensing of methane plays a vital role in the safety of underground coal mines. It has been demonstrated that changes in the atmosphere can occur suddenly and lead to explosive environments. Mining regulation requires that when the methane concentration at any methane sensor reaches 1.0 percent within the working place, a warning signal shall be given by the monitor (Title 30 CFR § 75.342(b)(1)). Also, regulations require that the methane monitor can deenergize electric equipment or shut down diesel-powered equipment when the methane concentration reaches 2.0% (Title 30 CFR § 75.342(c)(1)). Therefore, the continuous monitoring of the atmosphere in underground coal mines is the most important component for preventing the development of critical hazards such as fires or explosions. Due to the importance of gas sensing in underground mines, the objectives of this paper are: i) detail the current state of art in gas sensing in underground coal mines. ii) describe the concept of a new alternative for gas sensing in underground mining such as fiber-optic sensors (FOS) along with a FOS system developed at Virginia Tech. Finally, the proposal of a new platform of fiber distributed gas sensing and its applicability at the longwall face is presented.

A.3 Current Gas Sensors in Underground Coal Mines

Historically, methane sensors used in underground coal mines rely on catalytic heat of combustion [95]. These kinds of sensors are approved by MSHA to be used in underground coal mines [80]. In this section the concept of catalytic heat of combustion sensors along with its disadvantages are described.

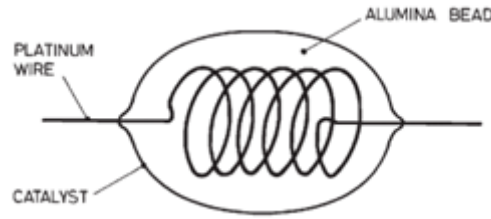


Figure A.1: Active bead (from [50])

A.3.1 Catalytic heat of combustion sensors

Catalytic heat of combustion sensors work under the principle of catalytic combustion. This phenomenon allows the oxidation reaction of combustible gas mixtures at lower temperatures to be sped up in the presence of a catalyst [80]. These sensors generally are composed of pellistors that are small solid-state devices. Pellistors can measure the energy released after an oxidation reaction of a gas or vapor. A pellistor consists of two “beads” referred to as an active bead and reference bead connected forming a Wheatstone circuit. The active bead consists of a coil of a metal wire in a refractory bead coated with a catalyst as shown in Figure A.1 [50]. It is worthy to mention that the passive bead has the same configuration of the active bead but it does not contain a catalyst and only it is used as reference of constant resistant.

When a combustible or flammable gas goes through the active bead, the coil provides enough heat to burn the gas (around 500°C) since electrical current is passed through the coil. The oxidation reaction occurs when gas molecules are in contact with the catalyst layer. The increase of temperature inside the active bead due to the combustion of the flammable gas changes the resistance of the platinum coil. The change of resistance is proportional to the heat, and consequently, to the amount of gas. Thus, gas concentration as a fraction of the lower explosive limit (%LEL) can be precisely determined. The determination of the change of resistance of the active bead is monitored by the Wheatstone bridge circuit which

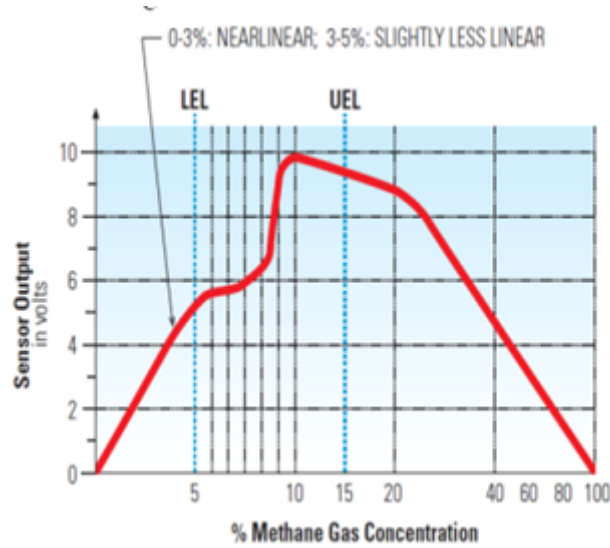
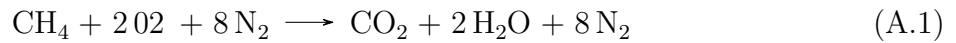


Figure A.2: Sensor output vs methane concentration (from [50])

generates an electrical signal proportional to the methane concentrations [95].

The oxidation reaction of methane inside the active bead is shown in Equation A.1. As mentioned previously the amount of methane concentration is matched to a sensor output in volts as shown in Figure 2 [50]. It is seen that for methane detection, the sensor output behaves linearly from 0% to 5% of methane. After 9% of methane the signal output increases sharply until 10%. After this peak point, the output signal decreases slowly until 20% of methane and drops sharply between 10% and 20%. This behavior limits the catalyst sensors to measure methane concentration only within the linear behavior.



Although catalytic heat of combustion sensors have been widely used and approved for permissible areas, these sensors are primarily electrically powered. This means that although they comply with MSHA requirements, should an atmosphere with 2% methane or greater develop, they must be deenergized, limiting the information available to operators, emer-

gency responders, and command centers. Additionally, catalytic sensors are generally limited to measurement up to the lower explosive limit (LEL) between 0 to 5% methane (linear region) [102]. Furthermore, it has been demonstrated that catalytic sensors require a minimum oxygen concentration of 12% for proper operation, which may not exist during mine emergency atmospheric conditions [102]. Finally, catalytic sensors can be sensitive to the presence of ethane, propane, and flammable gases such as hydrogen, producing inaccurate readings if these other hydrocarbons are present [40].

Due to the facts just mentioned, FOS are seen as an alternative for eliminating the disadvantages of catalytic sensors. In the following sections the concepts behind FOS will be discussed as well as developments of FOS and the proposal of a new platform of fiber distributed gas sensing and its applicability at the longwall face.

A.3.2 Description of fiber optic sensors (FOS)

FOS are a viable alternative for gas sensing in underground mining. FOS are intrinsically safe, electrically passive, and deployable in remote, isolated, hazardous, and limited spaces without human operators [23, 57, 87]. A fiber optic sensor is composed of an optical fiber connected to a light source, and is a thin, long piece of glass that consists of the cladding and the core where a light signal can travel over tens of miles as shown in Figure A.3. The cladding or outer layer confines the light to the core and provides mechanical protection. It is important to mention that other coating and/or jackets are often used for additional protection. The principle of FOS is based on the interaction of the optical fiber with its surroundings in which the light in the core will be encoded with useful information about the environment. FOS can measure different parameters such as temperature, vibration, pressure, strain, and gas concentration. It has been demonstrated that FOS have good

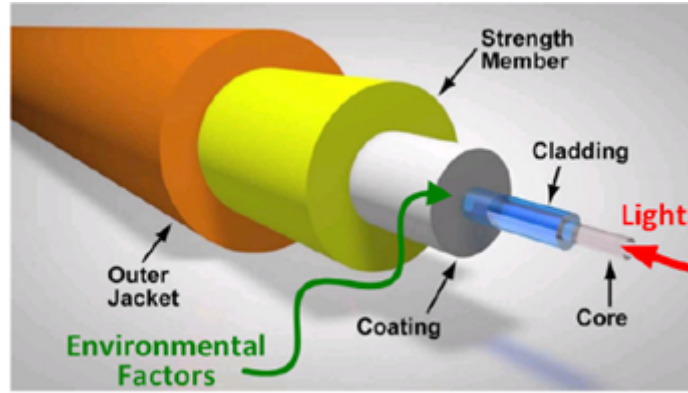


Figure A.3: Optical Fiber (from [87])

performance in extreme conditions and operations such as oil and gas boreholes, power plant boilers, and coal mines.

A.3.3 Methane FOS system with MSHA experimental permit developed at Virginia Tech

A point methane FOS system was developed in the Center for Photonics Technology (CPT) at Virginia Tech in collaboration with the Virginia Center for Coal and Energy Research (VCCER) [6]. This system consists of a control box, an optical fiber cable, and a sensor probe as shown in Figure A.4a. A gas cell is located inside the probe for measuring optical absorption by the gas (Figure A.4b). The light travelling through the gas cell from a transmitting fiber to a receiving fiber is absorbed by the gas, allowing for the determination of methane concentration. The measured values from the sensor have a linear relationship with the true diluted concentration of methane as shown in Figure A.5(a), which demonstrates the sensor works properly with a linear dependence up to methane concentration of 50%. Also, this sensor operates with a laser power of 0.01 W and 450 micrometers beam diameter, a power density that is 100 times lower than the thresholds of dust ignition published by

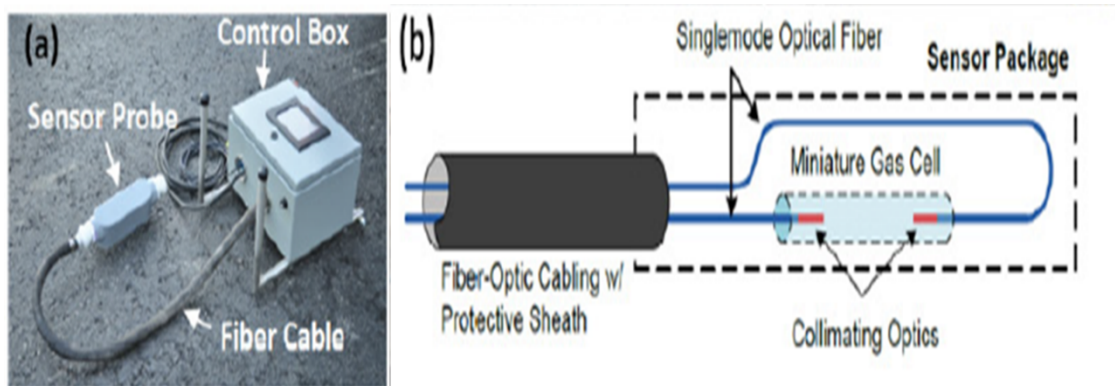


Figure A.4: CPT point methane fiber optic sensor. (a) Components. (b) Gas cell

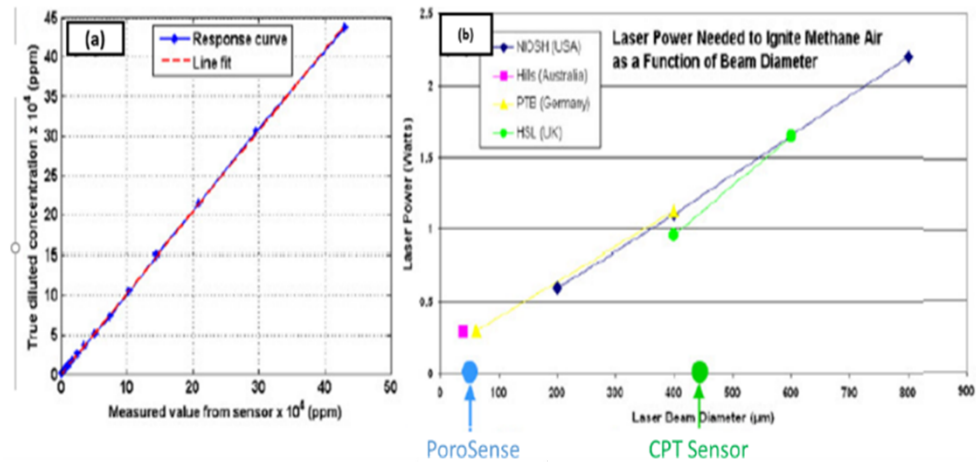


Figure A.5: (a) Measured value from sensor. (b) Laser power to ignite methane air as a function of beam diameter for different countries.

multiple countries as shown in Figure A.5b. The last fact demonstrates that this system is quite safe and electrically passive; - in fact, it could be safely left on when atmospheres develop beyond the statutory 2% methane level.

A.4 PoroSense: An intrinsically safe, distributed fiber-optic gas sensing platform for underground mines

The general idea of a potential new platform of fiber distributed gas sensing that may be implemented in underground mines is presented in this section. The system described is based on a previously mentioned mine-demonstrated experimental methane fiber sensor developed at the Center for Photonics Technology at Virginia Tech [6]. The projected system aims to develop a permissible platform with high functionality for underground coal mines. The use of a porous-clad optical fiber will be the novelty of this system, consequently called PoroSense. A single long optical fiber clad by 3D nano-porosity will be utilized, allowing only gases to penetrate and interact with the fiber core enabling gas sensing. Simultaneously, the 3D nano-porosity prevents dust particles from entering the fiber. This characteristic of PoroSense along with the known fiber-optic sensors electrical passivity represents a safer approach for sensing in underground mines providing improvements in safety, coverage, flexibility, and functionality.

The general idea of the PoroSense distributed sensing platform is shown in Figure A.6. In this approach, FOS are placed along the length of the fiber. This type of FOS is known as distributed fiber sensing. A typical distributed FOS works by sending a light pulse through the fiber in which a certain percentage of the pulse energy is reflected by each individual sensor. A detector will receive the amount of energy reflected by each sensor and will obtain the information for each location through decoding techniques. The advantage of distributed FOS is that it is scalable regarding the number of sensors, their density, and fiber length depending on the application requirements. Due to the two main characteristics mentioned regarding permissibility and distributed sensing, PoroSense platform will likely have a great acceptance in the mining field.

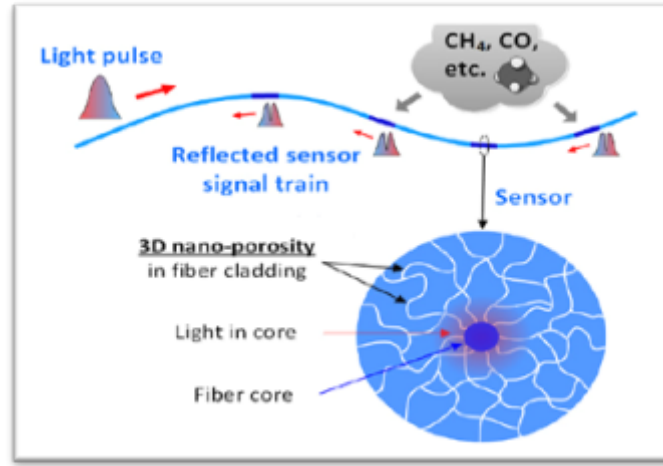


Figure A.6: Concept of the PoroSense platform

This novel platform is enabled by three techniques –porous-clad optical fiber (PCOF) with 3D Nano-porosity, pulsed laser absorption spectroscopy (PLAS) and spectral self-calibration (SSC). The first technique allows for intrinsic safety and rapid gas response, the second technique allows for fast response with regard to concentration detection, and the third technique for sensor crosstalk elimination. These three techniques working together represents a new distributed gas sensing approach:

- The PCOF is different to conventional fibers without porosity. Besides, it is different to conventional fiber with porosity only along the fiber length. The PCOF possesses a radial porosity allowing for instant gas access to the core and prevent gas diffusion between sensors.
- The PLAS offers fast distributed gas sensor interrogation allowing for all sensors to be interrogated by a single light pulse containing a broadened spectrum. Reflections from a sensor will be used for detection.
- The sensor cross talk will be eliminated through the SSC technique by taking the reflection ratio between the front and back of the sensor boundary to remove the

spectral signature of upstream sensors. This can be seen as a novel calibration concept well suited for gas sensing.

A.5 Applicability of optical fiber sensing technology for continuous and distributed sensing of gases at the longwall face, bleeder, and belt entries

As mentioned previously, longwall mining is an extraction method that produces large volumes of methane. Thus, characterization of methane levels is vital for the mine safety [49]. In this section, some important locations of longwall mining are selected for the installation of distributed FOS due to their potential for accumulation of methane and associated explosion, or high risk potential due to regular presence of miners. These locations are proposed based on knowledge and expertise in typical longwall ventilation system. However, ventilation and fire modeling would allow for more robust recommendations on sensor locations.

A.5.1 Longwall face and bleeders

Methane sensors are required at the return air end of the longwall face, and on the downwind end of the shearer according to Title 30 CFR 75.342(a)(2). It is also required that these monitors are able to give a warning signal at 1.0% methane concentration and be able to de-energize equipment at 2.0 percent methane concentration under Title 30 CFR 75.342 (b)(1) and (c)(1) as mentioned previously. These regulations match with the fact that the longwall face is a zone prone to have high methane concentrations, and, consequently a high risk for fires and explosion due to the high probability of ignition sources. Although methane

sensors at points have been used widely with success in longwall mining, the installation of the distributed fiber optic sensing along the longwall face would be more effective for the determination of methane profile along the longwall face as the panel is being extracted. Furthermore, the constant determination of methane profile could allow for the prediction of methane emission levels as well as the improvement of methane emission control strategies [21]; In this paper, it is proposed that a distributed FOS is installed behind the hydraulic jacks on the shields as shown in Figure A.7 (blue line). The advantage of this location is that there are already power and cables hanging, so it would allow for easy installation and relatively good protection for the sensor. Although slight vibrations or movements can be experienced by the sensor, distributed FOS is insensitive to vibrations due to the self-calibration capability. Additionally, a distributed FOS is recommended to be installed in the middle entry of both the headgate and tailgates of the longwall for outby sensing (see Figure A.7 green and orange lines).

On the other hand, longwall coal mines use bleeder systems to ventilate areas where panels and gobs connect, including sections where pillars have been mined-out. Ventilation hazards such as accumulation of methane and other gases, and dusts can be mitigated with an effective bleeder system in order to protect miners and active workings. Regulations require that bleeder systems are examined by a certified person. The certified person shall take readings of methane, oxygen and flowrate every seven days (Title 30 CFR 75.364 (a)(1)). The measurements must be taken at areas where air enters the worked-out area, the return split, and the measurement point locations (MPLs) Title 30 CFR 75.364 (a)(1-8). In addition to the regulations, it is important to take measurements at mined-out areas because methane flow paths and methane profiles in the bleeders can change as the longwall panel retreats and the panel is extracted, and as external environmental factors (e.g., pressure changes associated with weather fronts) change. Some of these changes occur due to airflow patterns

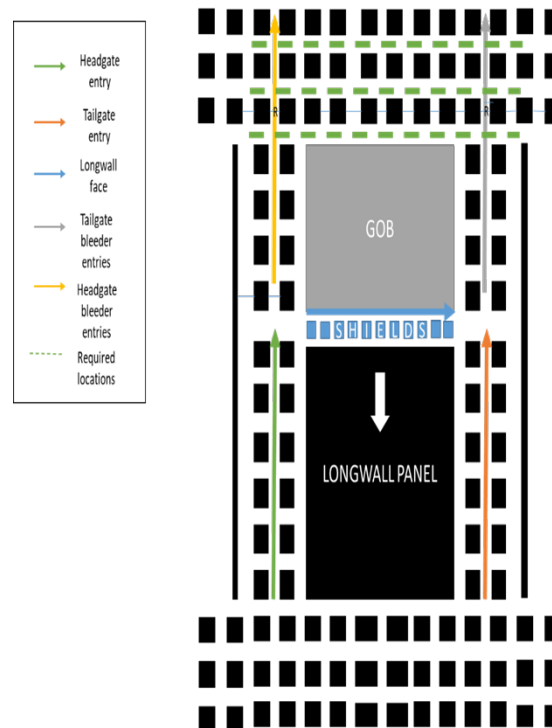


Figure A.7: Locations recommended to place distributed FOSes in longwall mining

in the gob which are affected by the compaction of the gob. For this reason, it is recommended to install distributed fiber-optic sensors in the middle entry of both the headgate bleeder entries and tailgate bleeder entries as shown in Figure A.7 (yellow and gray lines) since the inside entries become inaccessible. Furthermore, distributed FOS can be placed in all of the required locations of the bleeder system, and also can be placed before air enters the return air course as shown in Figure A.7 (dotted lines). A particular advantage of bleeder installation is that it allows for continuous monitoring of the area, rather than weekly point monitoring. Additionally, these areas tend to be recognized as hazardous areas for fire bosses who perform weekly monitoring – with continuous monitoring these personnel would have a better sense of conditions prior to entering, significantly improving their safety.

A.6 Conclusion

In longwall mining, large amounts of methane can be released at the working face and gob areas causing quick changes in the atmosphere which could lead to explosive environments. Due to this fact, real-time sensing of methane is one of the most important components in the safety of longwall underground coal mines. In this paper, gas sensors currently used in underground coal mines were described along with their limitations. Within these limitations, it was mentioned that catalytic sensors have some operational problems when the minimum oxygen concentration is lower than 12 percent in the air, the methane concentration does not fall between the range of 0 to 5 percent, or other gases such as ethane, propane, or flammable gases are present in the atmosphere. Furthermore, the limits and disadvantages of current sensors have been illustrated. FOS were shown as an alternative due their intrinsic safety, electrical passivity, and deployability in remote, isolated, hazardous, and limited spaces. This system builds upon a point FOS system previously developed. This system demonstrates good performance to measure methane concentrations up to 50 percent due to the linear dependence of the sensor for this concentration. Regarding the power, this sensor operates with a laser power of 0.01 W and 450 micrometers beam diameter, indicating that the power density is 100 times lower than the thresholds of dust ignition published by multiple countries. Also, the fundamental concepts and preliminary design of a new platform of fiber distributed gas sensing called PoroSense are outlined. Three different techniques such as 3D nano-porosity, pulsed laser absorption spectroscopy (PLAS) and spectral self-calibration (SSC) make the PoroSense platform a new distributed gas sensing approach with high potential. Different mine locations were proposed for the installation of the distributed fiber sensing technology based on knowledge and expertise in typical longwall ventilation systems. These locations were the working face and bleeder entries. However, ventilation and fire modeling would allow for more robust recommendations on sensor locations.