MSA
The Safety Company

Artificial Neural Network Technology

Leading to Enhanced False Alarm Suppression in Next-Generation Flame Detection

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Addressing false alarms has long been a persistent challenge with flame detection. Inaccurate classification of signals resembling flame patterns, though not inherently hazardous, can lead to facility shutdowns, operational reductions, and increased costs. Efforts have been underway to enhance detection schemes to mitigate false alarms without compromising the performance of genuine flame signal detection.

The range of potential flammable hazards is expansive and growing as materials and processes become more complex. Increasingly sophisticated flame sensing technologies with embedded intelligence are being used to reliably detect the most common potential ignition sources:

- Alcohols
- Chemicals
- Diesel
- Gasoline
- Kerosene
- Jet Fuels
- LNG/LPG
- Hydrogen
- n-Heptane
- Paper/Wood
- Fabrics
- Solvents

Some of the most challenging industrial environments for flame detection include:

- Automotive
- Aerospace
- Chemical Plants
- Power Generation
- Food/Beverage
- Oil/Gas Production
- Oil/Gas Distribution
- Oil/Gas Refineries
- Pharmaceuticals
- Textiles
- Warehouses
- Wood/Paper Plants

The popularity of optical IR flame detectors is due in large part to the fixed emission wavelengths of hydrocarbon flames in the infrared spectrum, which can be separated from most non-flame sources and analyzed in various domains. Classical optical hydrocarbon flame detectors are based on an expert system, where analog signals are collected from the optical sensors, converted into digital format, processed, and an output decision is reported on the presence of flame or lack thereof.

Although simple in appearance, the described model of flame detection becomes more complex when dealing with infrared data from real industrial environments. Infrared signals at flame emission wavelengths can be easily generated by a random motion, modulation of heated surfaces, hot air flow, arc welding, reflection off water surfaces, and other non-flame related environmental nuisances.

Optical flame detection manufacturers have attempted to resolve this limitation by using multiple sensors, each at a different wavelength. In addition to wavelength discrimination via use of multiple sensors, most optical detectors measure the temporal characteristics of the signal, thereby analyzing the flame flicker properties. Various signal-processing techniques such as correlation, taking ratios, frequency analysis, periodicity check, and threshold crossing are used in industrial flame detection to differentiate flames from non-flames.

The apparent difficulty of linear separation of flames from non-flame sources drives the usage of more sensors at a variety of wavelengths. In practice, this solution can be very laborious and difficult to implement as an expert system. So, there arises an interest in non-linear classification methods, in particular, artificial neural networks to distinguish between radiation from flame and non-flame sources of radiation.

In the solution described below, MSA's next generation MSIR Flame Detector utilizes multiple artificial neural networks *(ANNs)*, employing an ensemble method. These networks are trained with partially overlapping datasets and are complemented by expert filters. This combined approach is designed to significantly enhance the overall reduction of system false alarms.

Artificial Neural Networks-Based Decision Algorithm

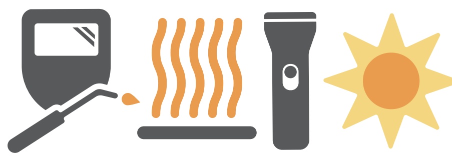
Selection of a neural network model involves optimizing parameters such as the number of neurons, activation function, learning rate, and learning algorithm. This careful consideration is an important step to set the stage to learn the differences in signal patterns from the input data.

A substantial amount of data has been collected, capturing a diverse array of events. An emphasis has been placed on events that historically posed challenges for flame detection algorithms, with a particular focus on false alarm scenarios.

These collected events are categorized into three distinct groups, with two of them earmarked for classification as flames:

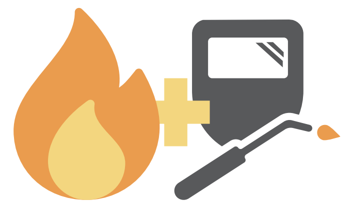
Flame Only

Encompassing a spectrum of different fuel types ignited either in pans or burners.



False Alarm Sources

Encompassing scenarios triggered by external factors such as sunlight, flashlights, heaters, and welders.



Interfered Performance

Encompassing scenarios where fuels are ignited in parallel with false alarm sources, introducing an even higher layer of complexity to the signal classification task.

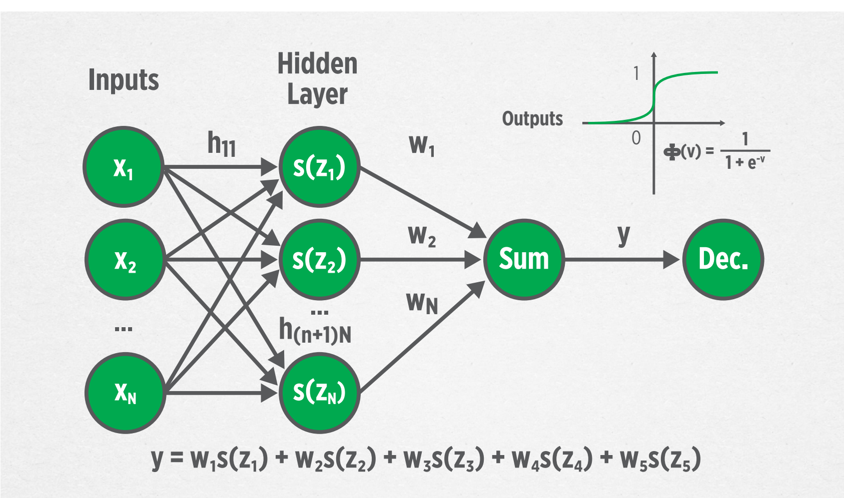


Figure 1: Typical ANN model architecture

The collected data undergoes a comprehensive pre-processing phase, transforming it to a set of features that are more suitable for the task of Artificial Neural Network *(ANN)* modeling process and subsequent flame classification. The ANN is strategically designed to learn and generalize from the data, with the goal of discriminating patterns and effectively classifying events based on their characteristics.

ANN Ensemble

In the realm of machine learning, the objective is to identify a model that optimally predicts the desired outcome. However, acknowledging the inherent complexity and diversity of real-world flame detection scenarios, relying solely on the connection weights *(output of ANN model training)* of a single ANN may not yield the best response across all situations.

To address this challenge, a layered approach is adopted. Instead of staking everything on a single model, a diverse array of models is created, each accounting for different subsections of the underlying data. It is worth noting that each ANN is trained on a different subset of a full data set. By tailoring the training process for each ANN to address nuances within its assigned subset, the system can become more resilient to certain false alarm triggers that may be prevalent within that specific domain.

The decision-making process of the system is a collaborative effort, leveraging an unanimity voting method from the outputs of three distinct ANNs. Thus, for the system to transition into an alarm from flame, all three ANN outputs must surpass a predefined flame threshold. This collective validation mechanism provides for a more comprehensive and reliable determination, mitigating the potential shortcomings of individual models and enhancing the detector's overall performance, especially in terms of false alarm suppression.

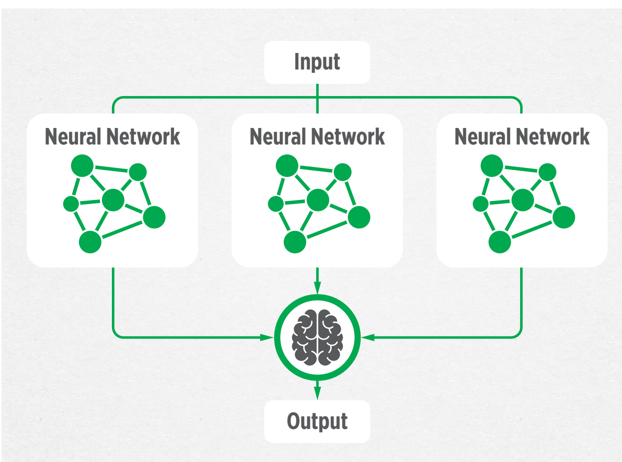


Figure 2: ANN ensemble

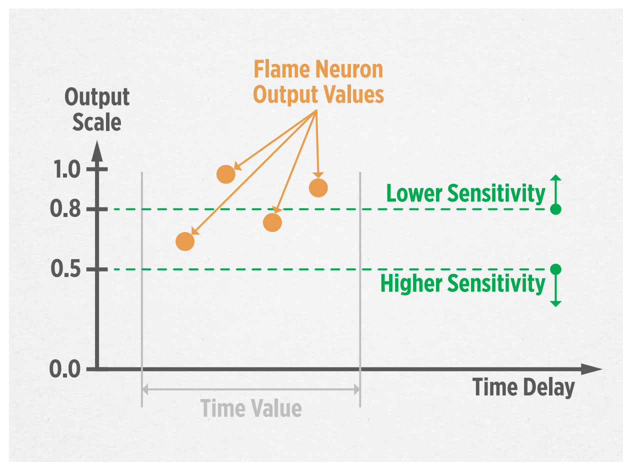


Figure 3: Unit sensitivity-based thresholding

Results

The utilization of the ANN ensemble method, coupled with a data collection strategy focused on assigning more weight to challenging false alarm triggers, has proven beneficial in achieving improvements in false alarm suppression. This approach outperforms a singular ANN model trained on evenly balanced data.

The strategic emphasis on common false alarm triggers during data collection amplifies the ensemble's sensitivity to subtle variations in the data, leading to a more nuanced and effective suppression of false alarms.

Conclusion

Artificial neural network technology is a proven solution across a wide range of industries. When ANN is combined with a multi-spectrum optical IR sensor package, it results in a powerful, next generation solution for flame detection with distinct advantages over other flame detection devices on the market today.

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