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# Sustainable Solutions: Monitoring Carbon Dioxide Emissions from Offshore Wind Power Welding through Deep Learning and Nondispersive Infrared Detection

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Taiwan, being an island, possesses abundant offshore resources, making it highly suitable for the development of offshore wind power. Welding plays a crucial role in the generation of offshore wind power because it enables the construction of steel structures that support offshore wind turbines. However, relevant personnel often fail to calculate the $CO_2$ emissions generated from welding because of the complexity of such calculation. Therefore, in this study, we designed a $CO_2$ detection module based on welding. $CO_2$ detection devices were placed at the air intake site of welding spaces to measure the $CO_2$ concentration during and after welding. The measured data were recorded, analyzed, and used for deep learning training with a deep neural network. Multiple detectors were required because of the substantial number of recorded data. Ensuring the reliable operation of fixed-point $CO_2$ detectors is crucial to measuring emissions before large-scale monitoring efforts. Additionally, we verified that the system consistently produces reliable results in multiple $CO_2$ measurement scenarios.

## 1. Introduction

The escalating severity of global warming has resulted in a considerable increase in focus on environmental conservation. Taiwan, being an island, possesses abundant offshore resources, and therefore, it is highly suitable for the development of offshore wind power, in which the energy of sea winds is harnessed to rotate turbine blades and eventually generate electricity. Wind power generation offers advantages such as zero carbon dioxide ($CO_2$) emissions, no fuel consumption, and minimal air pollution.

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Welding is integral to the establishment of offshore wind power plants because it enables the construction of steel structures that support entire offshore wind turbines. Kristiansen *et al.*[1] conducted welding on offshore turbines and discovered that their method satisfied good welding standards for both curved and flat sections. Jung *et al.*[2] used welding to analyze the toughness of offshore wind power support frames and proposed an algorithm for identifying optimal welding parameters. Farhan *et al.*[3] used decision theory to assist with the maintenance of welded structures on offshore wind turbines and identified the optimal inspection plan. Xu *et al.*[4] employed nondispersive infrared spectroscopy (NDIR) to detect carbon monoxide, $CO_2$, and propane and established an interference model involving these three gases. Zhou *et al.*[5] developed a $CO_2$ detection module using NDIR and a temperature and humidity compensation algorithm, and the model achieved an accuracy of ±0.9%. Xu *et al.*[6] also used NDIR to design a $CO_2$ detection module for harsh environments, and the model achieved an accuracy of ±0.1%. Sun *et al.*[7] proposed a multigas interference-free measurement method using two spectral light sources and NDIR, which resulted in a simple model structure and high accuracy. Rafique[8] detected the instantaneous density of $CO_2$ by using NDIR and achieved extremely high accuracy. Li *et al.*[9] employed deep neural networks (DNNs) to determine $CO_2$ concentrations with higher accuracy than traditional methods. Oh *et al.*[10] utilized DNNs to predict $CO_2$ capture, and the model led to lower costs and improved accuracy.

Offshore wind turbines are extremely large structures. When carbon emissions for such turbines are being calculated, the $CO_2$ generated from welding is often overlooked. Therefore, in this study, we measured and analyzed the $CO_2$ emissions from welding offshore wind turbines.

1. We proposed a new $CO_2$ detection system and expanded its range of applications.
2. We developed a $CO_2$ monitoring system specifically for welding applications.
3. We found that approximately 99% of the emissions from the welding process consist of $CO_2$.
4. We provided a baseline detection system for documenting $CO_2$ generated from welding.

## 2. System Architecture

### 2.1 $CO_2$ measurement principle

NDIR is a method used to measure gas concentrations by utilizing the absorption properties of infrared radiation. In this technique, an infrared beam is passed through the gas, and $CO_2$ molecules absorb specific wavelengths of this infrared light. A detector is placed on the other side of the infrared source that measures the remaining infrared radiation after it has passed through the gas. The concentration of the target gas can be estimated by comparing the intensity of the infrared radiation before and after it passes through the gas. The results are finally transmitted to a display. Vafaei and Amini[11] have used NDIR to analyze variations in $CO_2$ concentrations in environments with fluctuating temperatures and humidities, and they achieved a 99% accuracy rate. Akram *et al.*[12] devised an NDIR-based $CO_2$ detection system that was small, portable, and inexpensive. A schematic of the working principle of NDIR is illustrated in Fig. 1.

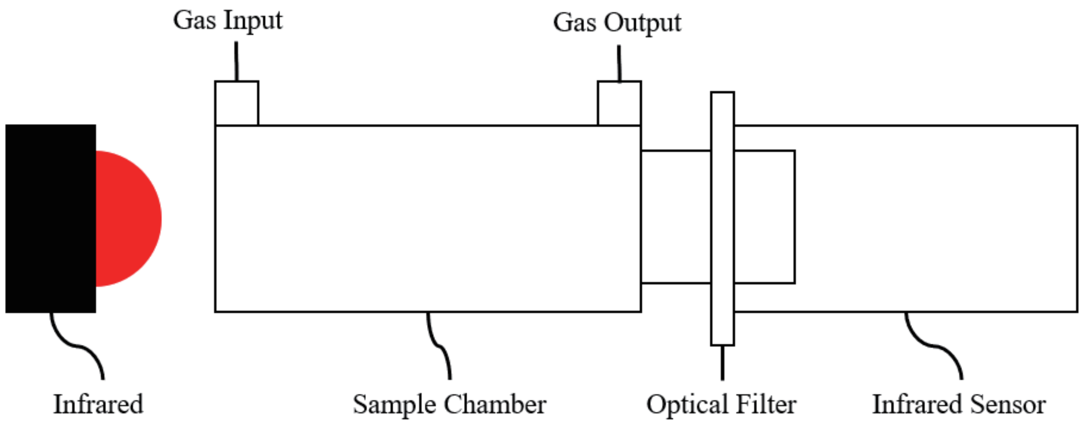


Fig. 1. (Color online) Schematic of working principle of NDIR.

### 2.2 DNNs

DNN are a type of neural network composed of input layers, hidden layers, and output layers. The input layer receives raw data, the hidden layers process these data through weighted connections and activation functions, extracting and learning features in the process, and the output layer produces a final output on the basis of the processed data. DNNs are trained using backpropagation, wherein the training results are compared with real data to compute the error between the actual and predicted values. This error is then used to adjust the DNN parameters to minimize the error. A schematic of the DNN used in this study is shown in Fig. 2. Tsaniyah *et al.*(13) utilized a DNN to predict $CO_2$ saturation levels with excellent accuracy. Zhang *et al.*(14) used a DNN to analyze $CO_2$ adsorption and corresponding materials, and they demonstrated that the model had effective prediction capabilities.

## 3. Experimental Setup

In this study, we designed a $CO_2$ detection module based on welding and conducted deep learning training using a DNN. The $CO_2$ detection device used in this experiment was a TFA Dostmann 31.5008.02 AIRCO2NTROL 5000 $CO_2$ meter with a data logger. This device was placed at the air intake site of the welding space to measure the $CO_2$ concentration during and after welding. A schematic of the experimental setup is shown in Fig. 3. The collected data on $CO_2$ emissions from welding are presented in Table 1.

## 4. Results and Discussion

We focused on measuring $CO_2$ emissions generated from welding. The measured values were subjected to deep learning using a DNN. Subsequently, 40, 60, 80, and 100% of the data were extracted separately, and deep learning training was conducted with epochs ranging from 10 to

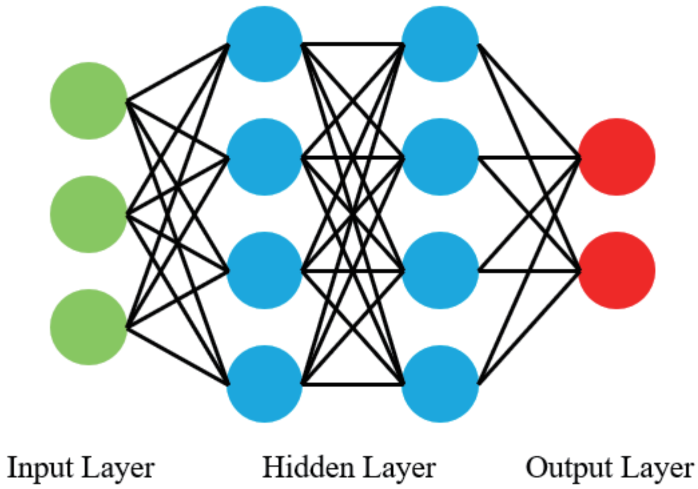


Fig. 2. (Color online) Schematic of DNN architecture.

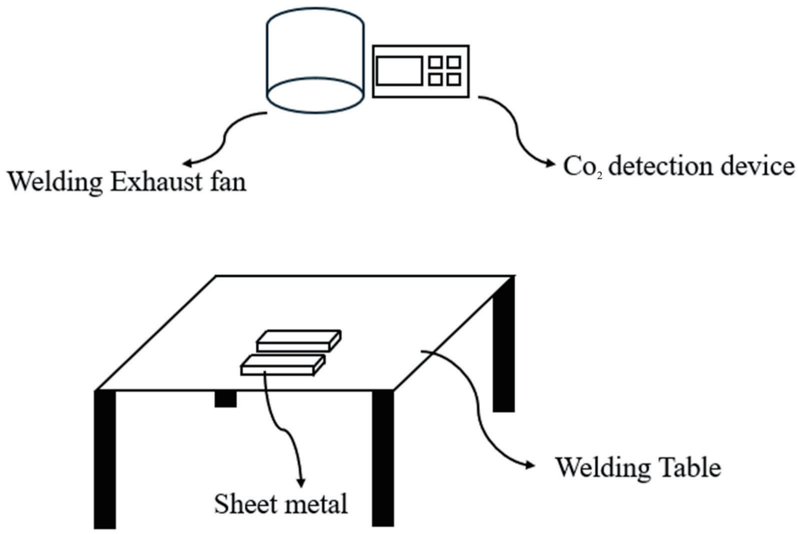


Fig. 3. Schematic of experimental setup for detecting $CO_2$.

Table 1
Training and testing data.

| | Quantity |
|---|---|
| 100% Training database | 2117 |
| 100% Testing database | 530 |
| 80% Training database | 1694 |
| 80% Testing database | 424 |
| 60% Training database | 1270 |
| 60% Testing database | 318 |
| 40% Training database | 847 |
| 40% Testing database | 212 |

100. The $CO_2$ emissions from welding were then statistically analyzed to facilitate the subsequent optimization of the processing workflow.

When 40% of the data were used for training (Fig. 4), the accuracy fluctuated; the 82% accuracy rate at epoch 10 dropped to 75% by epoch 30, rebounded to 82% by epoch 40, gradually improved between epochs 50 and 80 to reach a peak of 90%, slightly decreased to 89% at epoch 90, and finally increased to 95% at epoch 100.

When 60% of the data were used for training (Fig. 5), the accuracy fluctuated; the 85% accuracy rate at epoch 10 increased to 92% by epoch 20, slightly dropped to 87% by epoch 30, rebounded to 93% by epoch 40, steadily improved from 93 to 95% between epochs 50 and 70, slightly decreased to 91% by epoch 80, and finally climbed to 97% at epochs 90 and 100.

When 80% of the data were used for training (Fig. 6), the accuracy fluctuated; the 93% accuracy rate at epoch 10 steadily increased from 94 to 96% between epochs 20 and 50, decreased to 87% by epoch 60, improved from 96 to 98% between epochs 70 and 80, slightly declined to 97% by epoch 90, and finally returned to 98% at epoch 100.

When 100% of the data were used for training (Fig. 7), the accuracy fluctuated; the 87% accuracy rate at epoch 10 steadily increased from 95 to 98% between epochs 20 and 60, slightly declined to 96% by epoch 70, and improved from 97 to 99% between epochs 80 and 100.

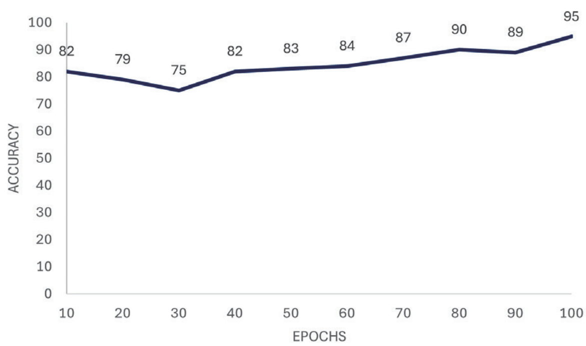


Fig. 4. (Color online) Accuracy when 40% of data were used.

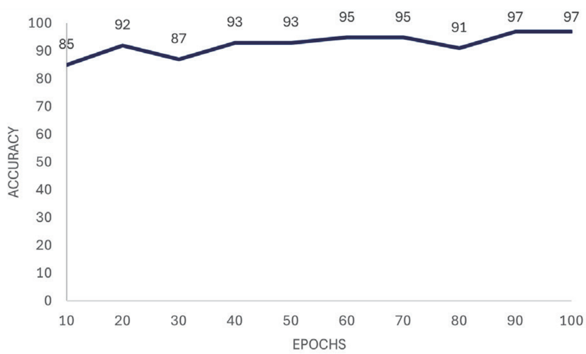


Fig. 5. (Color online) Accuracy when 60% of data were used.

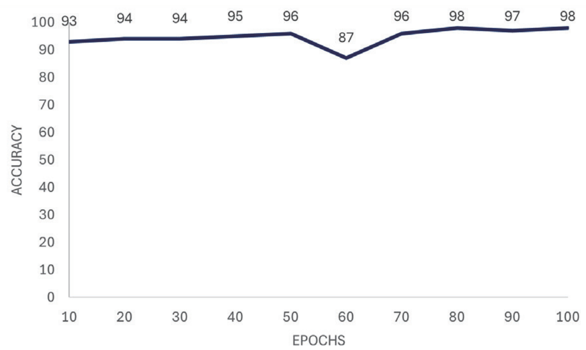


Fig. 6. (Color online) Accuracy when 80% of data were used.

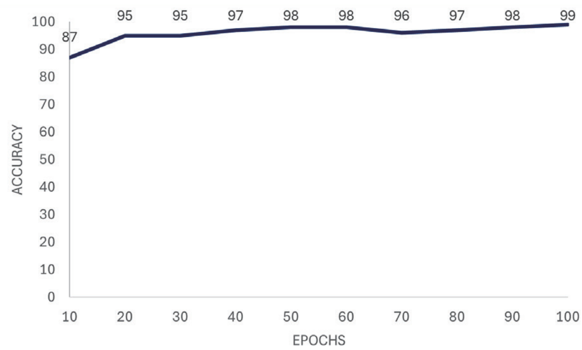


Fig. 7. (Color online) Accuracy when 100% of data were used.

## 5. Conclusion

In this study, we proposed a welding $CO_2$ emission detection system that utilizes DNN deep learning to monitor $CO_2$ concentrations during and after welding. Furthermore, we analyzed the accuracy of $CO_2$ monitoring at different data percentages. The conclusions drawn from the results of our comprehensive analysis are as follows:

1 We conducted DNN deep learning on collected data for prediction. The data were divided into groups of 40%, 60%, 80%, and 100% of the data. Deep learning training was conducted from epochs 10 to 100. The accuracy of training with different data percentages and epochs was used to develop a method for monitoring $CO_2$ emissions from welding.

2 The measured values of $CO_2$ emissions during and after welding were subjected to deep learning to enable the optimization of the processing procedure.

3 Such a model may enable the automatic detection of slight variations in $CO_2$ emissions during onsite welding and provide a recording and uploading system for the measured results.

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