

Chapter 5

Zero-Padding and Spatial Augmentation-Based Gas Sensor Node Optimization Approach in Resource-Constrained 6G-IoT Paradigm

5.1 Abstract

The ultra-low-power requirement is one of the key performance indicators in the Internet of Things (IoT) ecosystems and sixth-generation wireless communication technology (6G). The sensor nodes should be compatible with Artificial Intelligence (AI) models in such 6G-IoT networks to meet the upcoming innovations in this paradigm. The challenge rises whenever the sensor node is required to be deployed

in a resource-constrained environment since AI models require high computational capacity due to inherent complex architecture. In this chapter, we will discuss how a gas sensor node can be optimized to be power-efficient, and the high performance can be achieved using the synergy of an optimized sensor node and a lightweight Convolutional Neural Network (CNN). A gas sensor node consists of an array of non-selective gas sensors which are chosen randomly without any intuition about the optimal number. Hence, a gas sensor node essentially has some redundant sensor elements. A gas sensor array is optimized to be power-efficient by removing redundant gas sensor elements. While the deteriorated performance by this removal is compensated using a CNN incorporating zero-padding and spatial augmentation. The experimentation with this approach has been demonstrated to classify and quantify the four hazardous gases. The performance of the unoptimized gas sensor array has been taken as a “*baseline*” to compare the performance of the optimized gas sensor array. This approach reduced the power consumption of the gas sensor array to half. At the same time, classification and quantification were achieved with 100 percent accuracy, and a very low mean squared error (MSE). Consequently, our power-efficient optimization and lightweight CNN pave the way to deploy gas sensor nodes in the resource-constrained 6G-IoT paradigm. It is also suitable for edge intelligence reducing the computational complexity on edge.

5.2 Introduction

Internet of Things (IoT) in industrial paradigms requires power-efficient sensor nodes compatible with single-board controllers and processors [196]. Also, with the evolution of sixth-generation wireless communication technology (6G), power-efficient sensor nodes should be capable of working with Artificial Intelligence (AI)-based

models on the edge of the IoT-based networks [197, 198] (e.g., gas sensing systems). Moreover, a massive-scale deployment of 6G-driven IoT ecosystems results in high energy consumption and increasing CO emissions. Hence, the goal of eco-friendly 6G-IoT systems is to design and create energy-efficient sensor nodes, communication strategies, and protocols through optimization [198-200]. As an illustration, the 6G-based automation in Industry 4.0 essentially requires optimizing power requirements, Quality of Services (QoS), and other used resources [201]. Thus, designing green 6G-IoT systems using energy conservation strategies, renewable energy supplies, and energy harvesting methods would benefit the industries and society. The variety of gas sensor systems applications has been described in [202-206]. Since the number of non-selective gas sensor elements in a gas sensor node is chosen randomly, gas sensor systems carry redundant gas sensor elements that enhance the node's power consumption. The removal of such redundant gas sensor elements can be an approach to reduce the actual power consumption and make the gas sensor node power-efficient [207]. Thus, the optimized gas sensor node will become more acceptable to the resource-constrained 6G-IoT industrial paradigms. The optimization techniques to gas sensor nodes can be applied in both the hardware and the software context [207, 208].

The modern application of gas-sensing systems for hazardous gas monitoring in industrial ambiance recently employed wireless sensor networks (WSNs). Here, the sensor nodes are the primary power consumers; thereby, gas sensor nodes become constrained. Therefore, optimizing the power requirement without significant degradation in the node's performance becomes essential. Somov et al. (2014) have proposed an efficient sensing circuit design to optimize power requirements while retaining accuracy [207] to solve this issue. They presented their solution for gas concentration measurement using a single sensor through a voltage divider circuit

in contrast to the traditional Wheatstone bridge-based circuit. With this strategy, they reduced the requirement of two sensors up to one. Hence, the required power capacity by the sensing circuit is also reduced to half. Moreover, along with power optimization of a WSN node employing gas sensing, they also employ secure heating of gas sensors independent of the condition of ambience. Their approach significantly ensures energy savings. The gas sensor nodes used in gas sensing systems are onboard circuits requiring energy, memory, and computational capability. Analogous to this issue, Amarlingam et al. (2020) have used a signal processing-based compressed sensing (CS) for data aggregation to achieve energy efficiency suitable for resource-constrained IoT systems [208]. Their approach offers an optimal trade-off between power requirement and the computational complexity of the node. They have reported achievements of significant energy savings using their technique. Thus, the ongoing research aimed at sensor node optimization at different levels, viz., design of optimal sensing circuit and CS-aided data aggregation.

The real-time monitoring of hazardous gases/odors requires effective ubiquitous IoT systems for people's security and safety [209]. Specifically, in industrial ambience, detecting and estimating the obnoxious or hazardous gases/odors is inevitably required for the well-being of the workers [210-213]. However, non-selective metal oxide semiconductor (MOX) gas sensors are commercially cheaper compared to their peers but prone to consume significantly more power. Thereby, the removal of redundant physical gas sensors will help reduce the power requirements for the gas sensor node. However, such reduction may lead to degradation in the node's performance. If it happens, performance degradation can be compensated using AI-based data analytics. While solving this issue, the main challenge is to use lightweight approaches that enable "computation on edge." CNN-based learning for IoT systems that allows edge computing incorporation with IoTs can be seen through [214].

Also, the efficacy of CNNs has been reviewed in [215] for such edge computing.

Being inspired by the worldwide success of CNNs, Peng et al. (2018) have proposed a two-dimensional Deep CNN (DCNN) to classify the considered gases/odors. This DCNN architecture is composed of 38 layers and published with the name “GasNet” [162]. The proposed architecture of GasNet is relatively complex to classify the gases/odors, leading to high computational complexity. In contrast to a two-dimensional CNN, Zhao et al. (2019) have proposed a one-dimensional DCNN to classify the binary mixtures of ethylene, carbon monoxide, and methane [163]. Furthermore, a LeNet-5 architecture [167] has been modified by Wei et al. (2019) to classify carbon monoxide, methane, and their binary mixture [164]. Their approach is also headed towards consuming high computation capability. The discussed procedures are relatively complex, thereby unsuitable for resource-constrained environments. However, a relatively complex CNN architecture using a hybrid methodology is inevitably required while classifying the gases/odors using an extensively drifted dataset that can outperform by curtailing drift effects [168].

In this chapter, we have discussed the optimization of a gas sensor node where a gas sensor array employs four gas sensors. This optimization leads to a gas sensor node suitable for resource-constrained 6G-IoT applications. The effective power consumption by the gas sensor node is curtailed by removing the redundant gas sensor element(s) one by one, corresponding to redundancy. The performance degradation incurred on removing sensor elements is compensated using edge intelligence and advanced data pre-processing approaches. As evident from the recent literature, CNNs are being used to design intelligent gas sensor systems that outperform utilizing CNN’s inherent automatic extraction capability of salient features [162-164]. With this approach, we successfully optimized the gas sensor node; now, it can outperform using only two physical gas sensors and data analytics with zero

padding, spatial augmentation, and CNN. However, the responses of the removed sensor elements are replaced with zeroes to maintain the 2D shape of the input data vectors. Thus, the obtained primitive 2D input data vectors are then upscaled to attain a form of (6×6) using spatial augmentation. Using these upscaled (6×6) input data vectors, a simpler CNN is trained to classify and quantify the considered gases/odors. We achieve very high accuracy for the unknown test samples of the considered gases/odors.

We have presented the hypothesis to make the gas sensor node power-efficient by optimizing the gas sensor array consisting of four physical gas sensor elements. It has been tested for two different scenarios, viz., *(i) In the first case, the most redundant gas sensor element is identified, and its responses are replaced by zeroes. Thus, only three physical gas sensors play the role of consuming the power. (ii) In the second case, the two most redundant gas sensor elements are identified, and their responses are replaced by zeroes. Thus, only two physical gas sensors play the role of consuming the power.* Moreover, to identify the redundant gas sensor elements, we test the performance of the considered gas sensor array for all the possible combinations corresponding to both cases. At the same time, the performance of the gas sensor array with all four physical gas sensor elements has been taken as a “baseline” to compare the performance in both cases. These scenarios are briefly explained as follows:

Scenario 1: Optimization by Removing Most Redundant Gas Sensor Element (3 Physical and 1 Zero-Padded Virtual Sensor Element)

We have four possible cases in this scenario to identify the most redundant gas sensor element. Hence, the responses of one out of the four physical gas sensors are replaced by zero-padded values. The input data vectors with four elements are represented as (2×2) ; thus, obtained data vectors are then spatially augmented to achieve the

shape (6×6). These zero-padded and spatially augmented input data vectors are used to train a simpler CNN to classify and quantify unknown test samples of the considered gases. We achieve higher performance in this scenario, and the successful removal of the most redundant sensor element leads to 25% power-saving without significant degradation in the performance.

Scenario 2: Optimization by Removing Two Most Redundant Gas Sensor Elements (2 Physical and 2 Zero-Padded Virtual Sensor Elements)

In this scenario, six cases are possible to identify the two most redundant gas sensor elements. Hence, the responses of two out of the four physical gas sensor elements are replaced by zero-padded values. According to the procedure used in the previous scenario, we achieve the input vectors with dimensions (6×6). Similar to the last scenario, we use simpler CNN to obtain the experimental results for this scenario. Along with the high performance, the successful removal of the two most redundant sensor elements leads to 50% power-saving without significant degradation in the performance.

5.2.1 Motivation and Utilities for Presented Work

In the current scenario, the low-cost pollution monitoring system to detect and estimate the pollutants in indoor and outdoor environments became inevitable. These systems are being developed to deliver assured performance for better health and safety. Such systems require low-power, low-bandwidth, high-performance, and less complexity, to be supported by 6G-IoT for ubiquitous monitoring and rapid data gathering. Enabling edge intelligence to such sensor systems can deliver significantly high performance at lower bandwidth. On the other hand, in MOX-based gas sensor systems, incredibly high power is consumed, which poses design constraints. Also,

there is no rule to using the optimal number of MOX-based gas sensor elements in the gas sensor array, which results in redundancy and more power consumption. A significant reduction in consumed power by the gas sensor nodes can be achieved by removing redundant non-selective gas sensor elements and using CNNs for data analytics to compensate for the performance degradation. Instead of using a simpler CNN, various authors have used complex DCNNs challenging to be used on edge.

Leveraging the discussed opportunities and limitations, we have devised a novel approach. Here, a simpler CNN is applied to the data pre-processed by specialized data pre-processing procedures. With our proposed policy, the designed gas sensor systems can provide a power-efficient methodology suitable for resource-constrained 6G-IoT applications. Also, using a simple CNN makes it intelligent and compatible with the network's edge. To the best of our knowledge, the proposed approach for gas sensor node optimization can deliver high accuracy for classifying and quantifying gases/odors. It is the first work of its kind. Consequently, it also significantly reduces power consumption by the gas sensor node.

We can highlight the utilities of the proposed approach under the following headlines:

- ☞ To classify and quantify the considered gases/odors without significant degradation in performance, a gas sensor node can be optimized to be power-efficient using our novel approach.
- ☞ The power-efficient optimization of gas sensor nodes enables “computation on edge” for resource-constrained 6G-IoT applications.
- ☞ Although, we remove the redundant sensor elements during optimization. The trilogy of zero-padded virtual sensors, spatial augmentation, and a simpler

CNN reduces hardware cost and effective power consumption without significant deviation in the sensor node's performance.

- ☞ Our approach is straightforward and computationally less complex, making it well-suited for edge computation in resource-constrained systems.

5.3 Description of Used Dataset

The proposed approach for gas sensor node optimization has been demonstrated using a dataset consisting of responses from four gas sensor elements. These gas sensor response signatures are captured for four gases/odors, viz., acetone (*ace*), carbon tetrachloride (*car*), ethyl methyl ketone (*emk*), and xylene (*xyl*). Moreover, the corresponding gas sensor array embraces integrated gas sensing elements that have been fabricated using thick-film technology [151]. These sensing elements are fabricated by doping three different materials, viz., cadmium sulfide (*CdS*), molybdenum oxide (*MoO*), and zinc oxide (*ZnO*), into the base material of tin oxide (*SnO*₂). Further, the undoped tin oxide (*SnO*₂) has been taken as the fourth gas sensing element. Also, the details on the selection and extraction of the used dataset have been well described in [152], where Rajput et al. (2010) have used this dataset to classify the respective gases/odors using multilayer perceptron (MLP)-based Artificial Neural Networks (ANNs).

This dataset has also been used in [165, 184] to perform certain proposed data analytics for classifying gases/odors. It consists of 58 (*ace*: 10, *car*: 13, *emk*: 18, *xyl*: 17) raw data vectors acquired by capturing the steady-state responses using the discussed gas sensor array. This dataset is available in two sets of randomly selected samples having 42 and 16 samples, respectively. The first set having 42 samples (*ace*: 8, *car*: 10, *emk*: 12, *xyl*: 12) has been used for training purpose. While the

second set of 16 samples (*ace: 2, car: 3, emk: 6, xyl: 5*) is used for evaluation. The samples in both sets are pre-processed according to our proposed approach before use as training and testing datasets. Here, each sample represents a four-element data vector. All the data vectors have well-defined categorical labels (*ace, car, emk, xyl*) for target gases that are used for classification. Moreover, they also have continuous targets corresponding to the used percent concentrations (%conc.) that are utilized for quantification.

A schematic block diagram of the gas sensor array along with the blocks for data (pre-)processing is shown in Fig. 5.1(a)-(b) used for classifying and quantifying the considered gas samples. Furthermore, the raw sensor characteristics corresponding to training input data vectors for the considered gases/odors have been shown in Fig. 5.2(a)-(d).

5.4 Gas Sensor Systems for Resource-Constrained 6G-IoT Applications

The resource-constrained 6G-IoT applications essentially require the optimized use of resources which is desired at the node level of sensor systems [216]. The gas-sensing systems are designed considering that a gas sensor node should be capable of delivering high performance and consuming less energy, less computational power, and optimal hardware. The low power consumption by sensor systems enhances the viability of sensor-based mobile and wearable technologies that are evidently resource-constrained applications. Moreover, the evolving 6G-IoT applications are firmly prone to leverage edge intelligence, especially in resource-constrained environments.

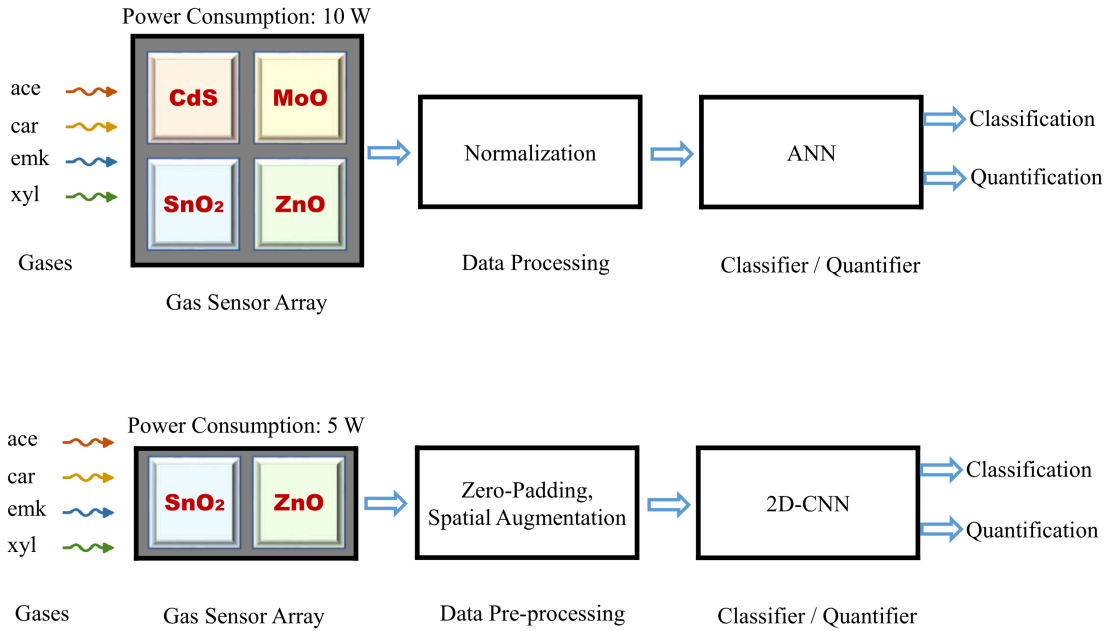


FIGURE 5.1: A schematic block diagrams of an electronic nose; (a) using traditional ANN which are too complex due to usage of only fully connected layers resulting in a large number of trainable parameters; (b) using the proposed sensor array optimization approach suitable for resource-constrained 6G-IoT scenarios incorporating a simpler 2D-CNN which results in less trainable parameters due to usage of convolutional layers than traditional ANN.

Several indoor, outdoor, and industrial paradigms require high-performance gas-sensing systems that should also be cheaper and power-efficient. It is also the point of importance that using optimal resources by gas-sensing systems in resource-constrained situations must not degrade the performance. If performance degradation is inevitable, then AI-based techniques are capable of compensating for that. Although, AI techniques also must be computationally efficient with straightforward architecture and configurations.

Our proposed approach manure the firm necessities of resource-constrained gas-sensing systems. Eventually, we successfully optimized the sensor node to be low-cost and power-efficient. Also, the use of a simpler CNN benefits the edge intelligence for resource-constrained applications by using low computational power.

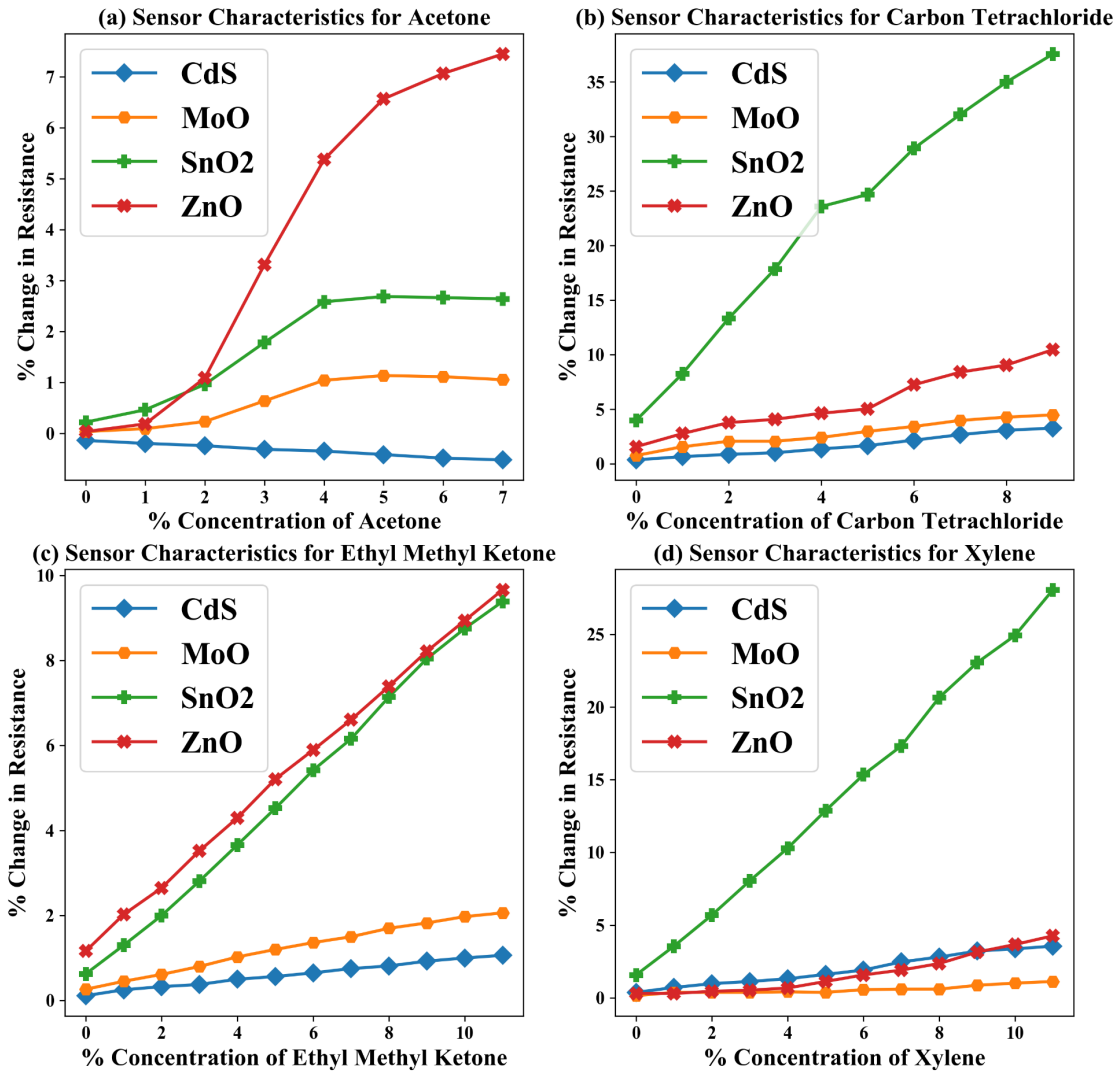


FIGURE 5.2: Percentage of Change in Resistance of Gas Sensor Element Vs. Percent Concentration of Considered Gas/Odor \forall the characteristics of four gas sensing elements of gas sensor array w.r.t. four hazardous gases/odors, viz., acetone, carbon tetrachloride, ethyl methyl ketone, and xylene.

The optimization has been achieved by removing redundant gas sensor elements that carry significant redundancy in responses due to their non-selective nature. With this strategy, our approach can be an alternative to reduce the actual power consumption by various sensor nodes.

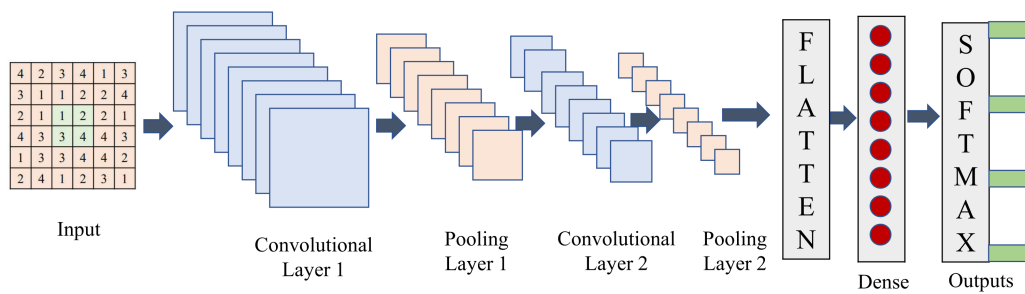
5.5 About Simpler 2D-CNN

Generally, 2D-CNN consists of several convolutional layers, and pooling layers followed simply by a multilayer perceptron architecture at the output end. The general architecture of a schematic 2D-CNN has been given in Fig. 5.3(a). A 2D-CNN witnessed widespread popularity, especially to classify the data represented in 2D format (e.g., images). Since images have highly correlated pixels, the pooling layers are essentially used to downscale the correlation that benefits to avoid overfitting. Recently, a high interest has been seen in the literature where various authors have started to use 2D-CNN for gas classification. However, they have used complex CNN architectures that seem precise for images instead of gases/odors.

By reducing the architecture complexity, the general architecture of a 2D-CNN has been customized to be simpler and well-suited for gas classification and quantification. The customized simpler 2D-CNN has been shown in Fig. 5.3(b). Being more straightforward, it consumes less computational power and provides high-performance while classifying and quantifying the considered hazardous gases. Moreover, the simpler 2D-CNN has been applied to pre-processed input data vectors. The customization described above is achieved by dropping the pooling layers from general architecture. Since the gas sensor responses, especially steady-state responses, are mutually independent; therefore, pooling layers do not serve a significant purpose. In contrast, images have various mutually correlated pixels; thereby, pooling layers are inevitably required while classifying the images. With this customization, the obtained architecture leads to the development of a simpler CNN. It is then trained using the corresponding pre-processed training dataset. The pre-processed input data vectors have input size (6×6) , which convolved with the kernels of size (3×3) at a single stride during the execution of the convolution process. With the result, we achieved convolved features of size (4×4) equal to

the number of kernels used. These features are obtained at the output of the 1st convolution layer. Using similar procedures, we achieve the convolved features of size (2×2) at the output of the 2nd convolution layer. Subsequently, these features are vectorized in a one-dimensional vector and used as the input to the upcoming fully-connected layer, which has 32 neurons. Next, the obtained resultants till this stage are forwarded to the softmax activation layer for classification and the linear activation layer for quantification of the considered gases/odors. Moreover, stochastic gradient descent (SGD) optimizer is used with a learning rate of 0.001, and the hyperbolic tangent (*tanh*) is used as the activation function for training.

(a) General architecture of a 2D-CNN.



(b) Proposed architecture of a simpler 2D-CNN.

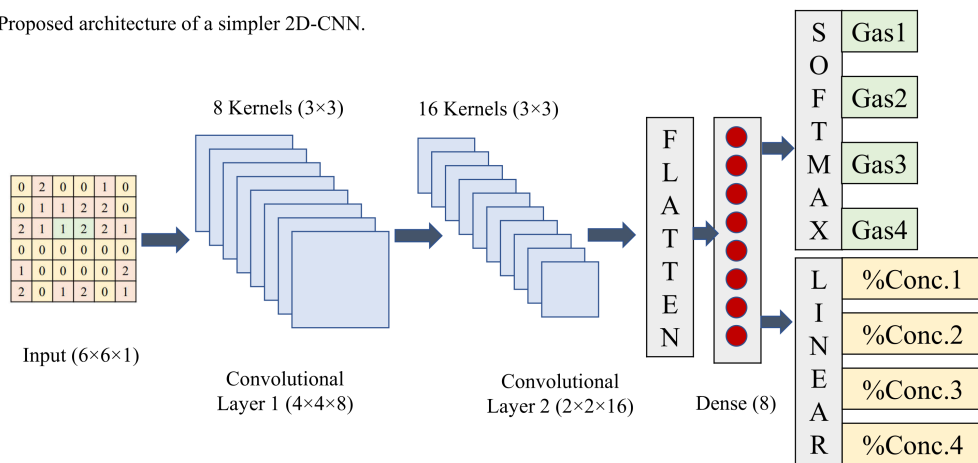


FIGURE 5.3: (a) The general architecture of 2D-CNN consisting of convolution and pooling layers, (b) Customized 2D-CNN for gas sensor node optimization well-suited for resource-constrained 6G-IoT applications.

5.6 Virtual Gas Sensors and Zero-Padding

The responses derived by applying normalization and transformation techniques to physical (actual) gas sensor responses are called virtual gas sensor responses. Thereby, these responses are considered to be obtained from virtual gas sensors (VGS). In [165], Mishra et al. (2017) have used normalized difference techniques to derive the VGS responses. They achieve six VGS responses from four physical gas sensor responses by applying respective mathematical formulations. In recent works [217], zero-padding and principal components-based virtual sensor approaches have been effectively presented to classify the gases/odors with high accuracy. Usage of VGS approaches enhances the data representation and information content of input data vectors that provides high-performance classification and quantification for the considered gases/odors. Each physical (actual) gas sensor element in a gas sensor array consumes considerable power. Being non-selective, MOX-based physical gas sensor elements respond to various gases simultaneously, thereby bearing significant redundancy in their signatures; they are also prone to consume considerable power. Therefore, removing redundant physical gas sensor elements reduces the power consumption and miniaturizes the hardware space suitable for resource-constrained applications. Removing physical gas sensor elements can be compensated by including the VGS approach at the level of data analytics. Accordingly, we have utilized the concept of VGS to optimize a physical gas sensor node suitable for resource-constrained gas sensor systems. This approach is also fruitful for sensor nodes working at the edge of the sensor network desiring optimal power requirements. While demonstrating our proposed policy, we have used zero-padding for VGS responses instead of determining them from physical gas sensor responses using some calculations. VGS responses represented by zero-padded elements save considerable computational power and provide better performance

without increasing the additional computational load. Moreover, substituting VGS in place of removed redundant physical gas sensors retains the size of input data vectors which enables further processing to make the input data vectors compatible with simpler 2D-CNN. Therefore, the reduced power requirement and less complex 2D-CNN are the utilities of our approach suitable for 6G-IoT applications operated in a resource-constrained environment.

Wherever the zero-padding scheme is applied, it provides the zero values to use as per requirement. Thus, zero-padding is an application-oriented technique to accomplish the task at hand. It is used for various configurations. For illustration, it is used to pad the zero values within or around the data. In [218], it has been used to retain the size of output features equal to the input features while applying linear convolution operation. Moreover, it is also used to maintain the size of data vectors when they occur with variable sizes or missing values during real-time data streaming. Data sparsing can also be achieved using zero-padding by replacing the nominal values with zeroes. In [219], various configurations of padding can be studied.

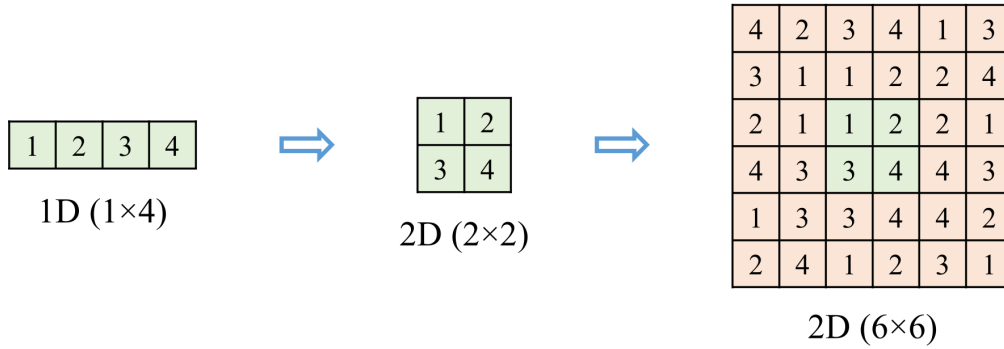
5.7 Contextual Outline of Spatial Augmentation

In our work, we use four physical gas sensor responses that result in each data vector having four elements. However, we remove redundant physical sensors, but their responses are replaced by zeroes using zero-padding that retains the size of data vectors. Thus, obtained data vectors are still incompatible with 2D-CNN. For further upscaling of data vectors, we use spatial augmentation so that the dimensions of input data vectors become compatible with the used simple 2D-CNN. In our experiment, the used dataset consists of responses obtained from a gas sensor array

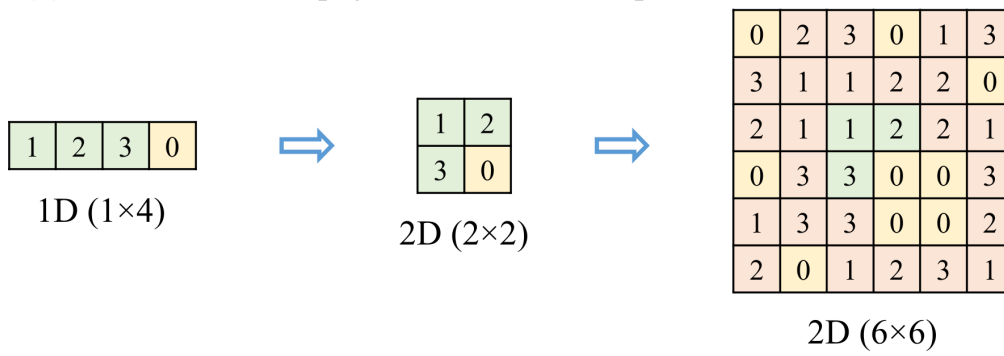
having four sensing elements. Hence, as discussed above, we can represent each data vector of size 4 in a 2D shape as (2×2) . With this input size, a 2D kernel of size (3×3) cannot operate at all. Therefore, we use spatial augmentation on (2×2) input data that upscale the size spatially by three times, i.e., (6×6) . Onwards the (3×3) kernels can be appropriately operated to extract the salient features during the linear convolution operation. The spatial augmentation can be applied to any 2D-squared data, e.g., (2×2) , (3×3) , (4×4) , and so on. The graphical representation of spatial augmentation is shown neatly in Fig. 5.4(a)-(c). It is a well-published technique used for different purposes based on mirror mosaicking [156, 184].

In this work, the used dataset contains the responses captured by four-physical gas sensors. Hence, each raw data vector has four elements, and it can also be represented in the 2D-squared format as (2×2) without any hassle. If the number of gas sensor elements used in any gas sensor array is not equal to a perfect square number, then the resultant data vectors cannot be represented in a 2D-squared format. The representation of data vectors in 2D-squared form is essentially required to implement the spatial augmentation that upscales the data vectors. Such upscaled 2D data inputs are compatible with the simpler 2D-CNN and allow the linear convolution operation to be executed appropriately to extract salient features. Therefore, we have presented a generalized algorithm to implement spatial augmentation in both cases, whether a gas sensor array possessed the gas sensor elements equal to a perfect square number or not. This algorithm has been mentioned step by step in the forthcoming text.

(a) Baseline: four physical sensor elements



(b) Scenario 1: three physical and one zero-padded virtual sensor element



(c) Scenario 2: two physical and two zero-padded virtual sensor elements

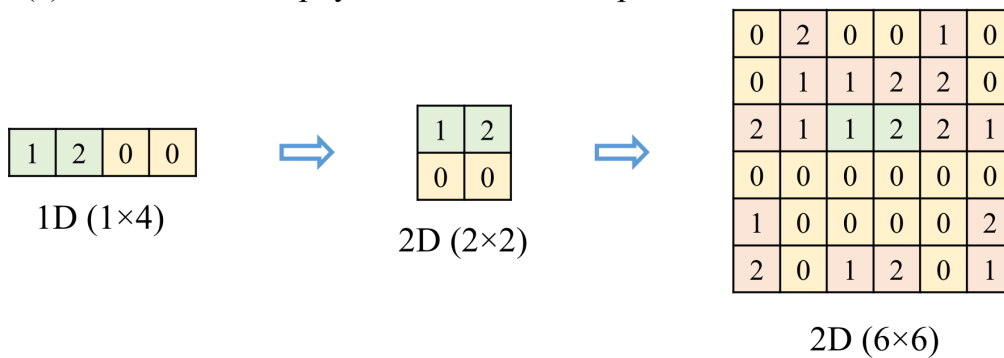


FIGURE 5.4: Augmentation procedure of four-element data vectors for (a) Baseline: Unoptimized gas sensor array, (b) Scenario 1: The removal of most redundant physical gas sensor element, (c) Scenario 2: The removal of two most redundant physical gas sensor elements.

Algorithm: General Procedure of Spatial Augmentation	
	<i>function</i> Spatial Augmentation (S)
	Input: S is the number of physical gas sensor elements in the gas sensor array (OR) is the length of raw data vectors
1	Output: Spatially augmented data vectors in 2D format suitable to use as the input to the simpler 2D-CNN
2	BEGIN
3	IF S is a perfect square number
4	Represent the data vectors in 2D-squared format of size: $[\sqrt{S} \times \sqrt{S}]$
5	Now augment these data vectors spatially as shown in Fig. 5.4 to upscale to the size: $[(3 \times \sqrt{S}) \times (3 \times \sqrt{S})]$
6	ELSE
7	Determine the number of required virtual sensors (α) to make the total number of sensors elements (physical and virtual) equal to the nearest perfect square number
8	After including the virtual sensors, the total number of sensor elements (physical and virtual) becomes $[(S + \alpha)]$ which is a perfect square number
9	Represent thus obtained data vectors in 2D-squared format of size: $[\sqrt{(S + \alpha)} \times \sqrt{(S + \alpha)}]$
10	Now augment these data vectors spatially as shown in Fig. 5.4 to upscale to the size: $[(3 \times \sqrt{(S + \alpha)}) \times (3 \times \sqrt{(S + \alpha)})]$
11	STOP

5.8 Experimental Cases for Baseline, Scenario 1, and Scenario 2

A gas sensor array with four gas sensing elements has been considered in our work. Also, a MOX-based gas sensor element typically consumes 500 mA at 5V (2.5 Watts). Hence, the gas sensor array requires an adequate power of 10 Watts. Our methodology reduces the use of redundant physical gas sensors from the array with the synergy of zero-padding, spatial augmentation, and a simpler 2D-CNN. This simpler CNN has been trained to classify and quantify the considered gases/odors. Cutting the power usage, paving the way to use a simpler 2D-CNN at the edge, and

enabling lightweight computational load, makes our approach suitable for resource-constrained 6G-IoT applications.

Primarily, the responses obtained from a gas sensor array with four physical gas sensing elements have been used to classify and quantify the considered gases/odors. Moreover, the obtained best performance for accurate classification and quantification using our approach has been considered the response of a best-performing gas sensor system. Since this performance is obtained while utilizing the responses from all four physical gas sensor elements, it has been referred to as the performance of a *Baseline Experiment*. Next, we remove the responses of any of the physical gas sensors and pad the zeroes in place of them. Such padded responses are then spatially augmented. These augmented inputs are used to train the same simpler 2D-CNN that classifies and quantifies the considered gases/odors. In this scenario, four experiments are conducted for four possible cases by removing physical gas sensor elements one by one. These experiments have been referred to as *Scenario 1 Experiment*. In this scenario, the best performing case is observed for accurate classification and quantification, along with identifying the most redundant physical gas sensor element. Subsequently, we remove the responses of any two physical gas sensor elements at a time and place zeroes at their locations. Similar to the previous scenario, such padded responses are spatially augmented and followed by the experiment to classify and quantify the considered gases/odors. In this scenario, six experiments are conducted for six possible cases by removing physical gas sensor elements two at a time. These experiments have been referred to as *Scenario 2 Experiment*. In this scenario, the best performing case is observed for accurate classification and quantification, along with identifying the two most redundant physical gas sensor elements. The rest detail of all the scenarios has been discussed in the forthcoming section.

5.9 Results

As previously has been discussed, three scenarios have been experimented with possible cases to demonstrate the effectiveness of the proposed methodology. We have analyzed multiple instances to achieve the best performance supporting high-performance gas sensing systems design. While testing under the quoted scenarios, we have compared the undertaken performance metrics, and significant remarks have been noted to develop an effective gas sensing system.

5.9.1 Experiment 1: Baseline (While Classifying and Quantifying the Considered Gases/Odors Using Responses of All Four Physical Gas Sensor Elements)

This baseline experiment considers the responses of four physical gas sensor elements integrated with the referred gas sensor array to classify and quantify the gases/odors. These responses have been recorded for corresponding steady-states. Due to obtained from four sensing elements, each data vector in responses is represented by a (2×2) 2D-squared array. Subsequently, we have applied spatial augmentation to upscale the array (2×2) following the algorithm presented in Section 5.7. Consequently, we achieve a spatially augmented array of size (6×6) suitable for a simpler 2D-CNN. Observing Fig 5.4., we can say that the raw data vectors having four elements have been upscaled to have 36 elements. These upscaled data vectors in 2D-squared format, i.e., (6×6) , have been used to train the CNN depicted in Fig. 5.3(b). The corresponding training dataset consists of 42 input samples of size (6×6) along with their targets. Subsequently, the trained CNN is evaluated for 16 unknown test samples (i.e., that were not used during the training). These 16

test samples also have the size of (6×6) . While testing, we achieve probability fractions for the respective target for classification and estimated concentration for targeted gas/odor for quantification. In this scenario, we get accurate classification results and estimated concentration with a very low mean squared error (MSE) for quantification. These baseline performances have been shown in Table 5.1.

TABLE 5.1: Performance Metrics for Baseline, Scenario 1, and Scenario 2 Experiments

Experiments (Scenario/Case)	Physical Gas Sensing Elements	Classification Accuracy (%) & Quantification MSE
Baseline	<i>CdS, MoO, SnO₂, ZnO</i>	100 & $(7.61 \pm 1.66) \times 10^{-3}$
1/1	<i>CdS, MoO, SnO₂</i>	100 & $(1.15 \pm 0.35) \times 10^{-2}$
1/2	<i>CdS, MoO, ZnO</i>	100 & $(4.01 \pm 0.53) \times 10^{-2}$
1/3	<i>CdS, SnO₂, ZnO</i>	100 & $(7.02 \pm 0.86) \times 10^{-3}$
1/4	<i>MoO, SnO₂, ZnO</i>	100 & $(1.43 \pm 0.21) \times 10^{-2}$
2/1	<i>CdS, MoO</i>	100 & $(3.01 \pm 0.16) \times 10^{-0}$
2/2	<i>CdS, SnO₂</i>	100 & $(1.42 \pm 0.33) \times 10^{-1}$
2/3	<i>CdS, ZnO</i>	100 & $(2.43 \pm 0.40) \times 10^{-2}$
2/4	<i>MoO, SnO₂</i>	100 & $(1.68 \pm 0.19) \times 10^{-1}$
2/5	<i>MoO, ZnO</i>	100 & $(3.17 \pm 0.91) \times 10^{-1}$
2/6	<i>SnO₂, ZnO</i>	100 & $(1.64 \pm 0.38) \times 10^{-2}$

In this baseline experiment, trained CNN results in the best performance with 100 percent accuracy for classification. At the same time, we achieved the quantification performance with a very low MSE of 5.86×10^{-3} during the evaluation of 16 unknown test samples. Moreover, Fig. 5.5 shows the sample-wise quantification performance. In this case, the maximum and the minimum errors are achieved at 3.61×10^{-2} and 4.01×10^{-5} , respectively, obtained during quantification. Since we have used all the physical gas sensor elements, the gas sensor array approximately consumes a power of 10 Watts. This power consumption has also been used as a baseline to compare the optimized gas sensor array.

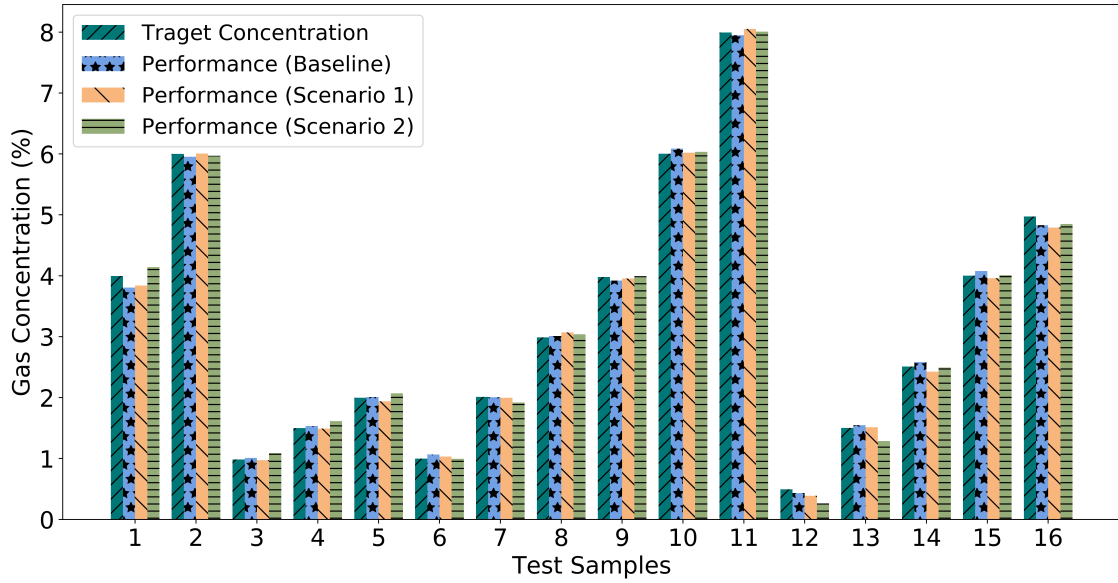


FIGURE 5.5: Sample-wise quantification performance for test samples in terms of actual vs predicted percent concentration during best observation of Baseline, Scenario 1, and Scenario 2 experiments.

5.9.2 Experiment 2: Scenario 1 (While Classifying and Quantifying the Considered Gases/Odors Using Responses of Three Physical Gas Sensor Elements & One Virtual Sensor Element)

In Scenario 1 experiments, three out of four physical gas sensor elements are considered, while the responses of the rest physical gas sensor element are replaced with zeroes using zero-padding. There is the possibility of only four combinations to replace one physical gas sensor element. Since the removed physical gas sensor element is substituted by zero-padding, it retains the data vectors' size and shape. As discussed in the baseline experiment, following the procedure shown in Fig. 5.4, we transform the data vectors in 2D-squared format with size (6×6) . Thus, spatially augmented data vectors create the training and testing datasets with sizes $(42 \times 6 \times 6)$ and $(16 \times 6 \times 6)$, respectively. Such obtained data vectors having dimensions

(6×6) are used to train the CNN depicted in Fig. 5.3(b). The trained CNN with 42 samples is then tested for 16 unknown test samples. With the results, classification is obtained with correctly classified instances. The actual and predicted targets for classification performance have been shown in Fig. 5.6. Moreover, to show the quantification performance, MSE for all possible cases in this scenario has been mentioned in Table 5.1.

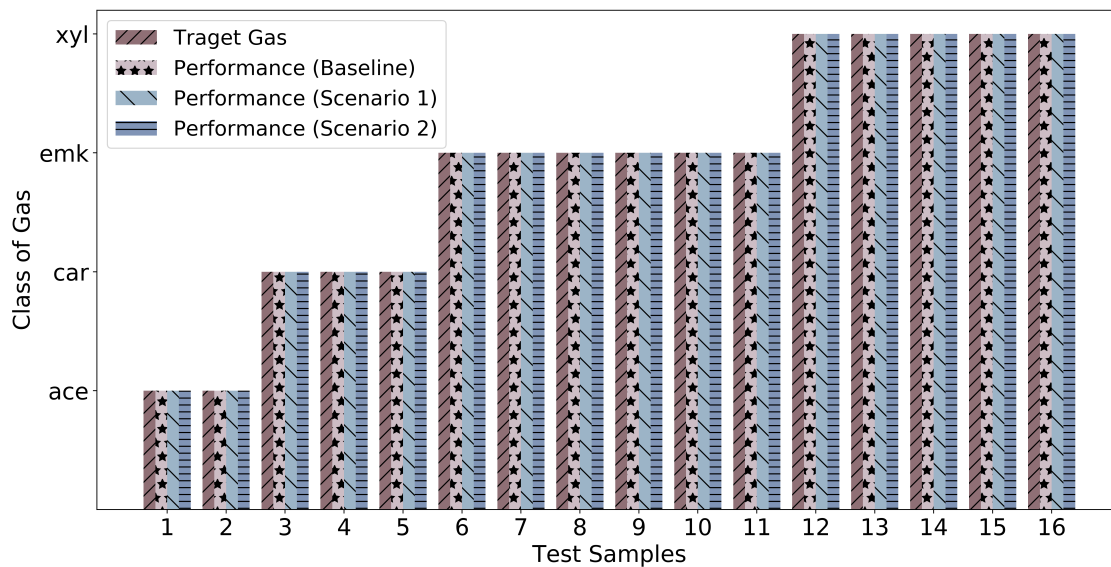


FIGURE 5.6: Sample-wise classification performance for test samples in terms of actual vs predicted targets during Baseline, Scenario 1, and Scenario 2 experiments.

We achieve accurately-classified test samples for all the possible experiments in this scenario. Thus, it is evident that we can still retain the classification performance even using only three physical gas sensor elements. In the best performing case for quantification, the achieved MSE is 5.82×10^{-3} , while the maximum and minimum errors are reached at 3.25×10^{-2} and 2.93×10^{-5} , respectively. The actual and predicted targets for quantification performance have been shown in Fig. 5.5. With this removal of one physical gas sensor element, the adequate power consumption by the gas sensor array is reduced by 25%. Along with this advantage, we

can also retain high performance for both the classification and quantification while evaluating 16 unknown test samples (not used during the training of the CNN).

5.9.3 Experiment 3: Scenario 2 (While Classifying and Quantifying the Considered Gases/Odors Using Responses of Two Physical Gas Sensor Elements & Two Virtual Sensor Elements)

In this scenario, the responses of two of the four physical gas sensor elements are taken as they are, while the rest of the two are replaced with zero-padded responses. In this policy, the data vectors retain their size and shape unchanged. Subsequently, spatial augmentation is applied to these data vectors of both training and testing datasets. This scenario sees six possible cases to replace the two physical gas sensor elements. We achieved 100 percent accurate classification in this scenario, as shown in Fig. 5.6. At the same time, the obtained MSE for quantification in these cases is shown in Table 5.1. In this scenario, the best performance has been observed in the 6th case. We achieve 1.12×10^{-2} MSE for quantification, while sample-wise quantification performances have been shown in Fig. 5.5. While evaluating the test samples, the maximum and minimum errors are obtained as 5.34×10^{-2} and 5.15×10^{-6} , respectively. Hence, it is evident that we can retain the classification performance even after removing the two physical gas sensor elements. Also, better performances have been achieved for quantification without significant degradation. In addition to achieving high performance, the removal of two physical gas sensor elements leads to a reduction in adequate power consumption of the gas sensor array by 50%.

Consequently, we achieve accurate classification results for all 11 experiments (Baseline, four experiments under Scenario 1, and six experiments under Scenario 2). Moreover, MSEs for quantification in Scenario 1 and Scenario 2's best cases, along with the Baseline, have been shown in Fig. 5.7. The insight for removing redundant physical gas sensor elements is drawn from the performance analysis. No sense has been drawn from Fig. 5.2 directly, which shows only the element-wise sensor characteristics. Observing Table 5.1, *MoO* is found to be the most redundant physical gas sensor element since its removal least affects the performance. Similarly, while removing two physical gas sensor elements at a time, it is found that *MoO* and *CdS* are the two most redundant sensor elements out of the four that least affect the performance. Accordingly, we can retain the performance without significant degradation. Also, we can reduce the effective power requirement by 25% and 50%, respectively, in Scenario 1 and Scenario 2. Thus, using our methodology, a gas sensor node can effectively be optimized for power and hardware requirements while retaining its performance. This policy is well-suited for resource-constrained 6G-IoT applications.

5.10 Discussion

As discussed, we have performed three broad experiments for Baseline, Scenario 1, and Scenario 2. The baseline experiment has been performed using the responses of all four physical gas sensor elements, where the corresponding gas sensor array adequately consumes 10 Watts of power (2.5 Watts by each physical gas sensor element). Here, classification has been achieved with 100% accuracy, while the quantification performance has been achieved with squared error up to five places

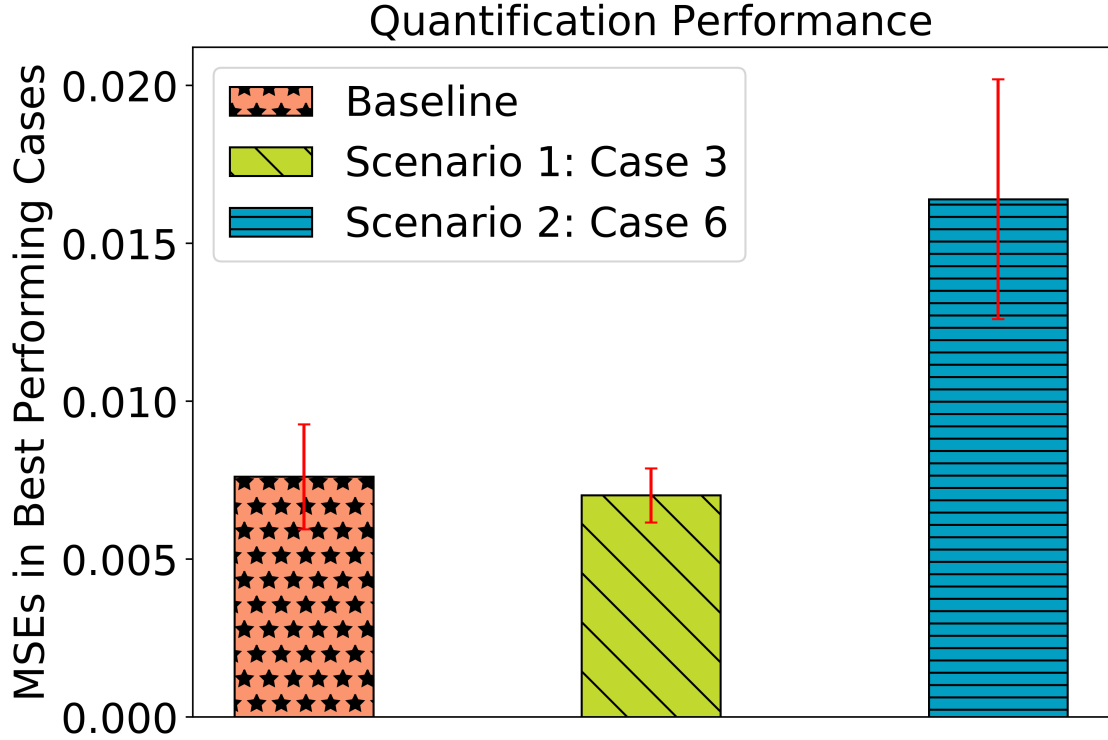


FIGURE 5.7: Quantification MSEs in Baseline, Scenario 1 / Case 3, and Scenario 2 / Case 6 experiments.

of the decimal. With the conducted performance analysis, it is evident that using our approach, the considered gas sensor array has been optimized to consume only 5 Watts of power (while saving 50% of power). Additionally, we can identify the most redundant (MoO) as well as most significant (SnO_2) physical gas sensor element based on performed data analytics. Hence, to save 25% of power, we can safely remove the most redundant physical gas sensor element while retaining the performance. Moreover, the gas sensor array has been optimized to reduce the effective power consumption by 50%, removing the two most redundant physical gas sensor elements (e.g., CdS and MoO). This optimized gas sensor array using our approach can still provide accurate classification. In addition to classification, the quantification performance has also been retained without significant degradation. Thus, our policy recommends that the gas sensor nodes can be optimized to

be power-efficient, cost-efficient, miniaturized, and intelligent solutions suitable for resource-constrained applications.

The conceptualization of ubiquitous 6G-IoT applications paves the way for enabling innovative and intelligent solutions for large-scale and resource-constrained environments. Ultra-low-power requirement is one of the key performance indicators in the 6G-IoT paradigms. A gas sensor array is a primary component of the gas sensor node that consumes a more significant chunk of the power supply. An approximated chart for power consumption distribution in a gas sensor node has been shown in Fig. 5.8(a)-(b). The reduction in consumed power and retaining high performance are the two saliences of our approach. Using the considered dataset, predecessors have limited their works only up to high-performance classification results. At the same time, our proposed novel scheme provides hardware efficiency, cost-efficiency, and power efficiency, along with high performance.

5.11 Conclusion

As the experiments demonstrate, we can achieve the optimization of gas sensor nodes by removing the redundant physical gas sensor elements from the array. This optimization makes salient features suitable for the resource-constrained scenarios in 6G-IoT applications. With our proposed specialized data maneuvering and a simpler 2D-CNN, the inevitable performance degradation that occurred due to the removal of physical gas sensor elements can be compensated. Thus, we have successfully optimized gas sensor node for data and resource-constrained applications. Moreover, removing redundant physical gas sensor elements results in less hardware requirement, and the optimized gas sensor node does not compromise the performance incorporating our proposed methodology. It enables the use of gas sensor

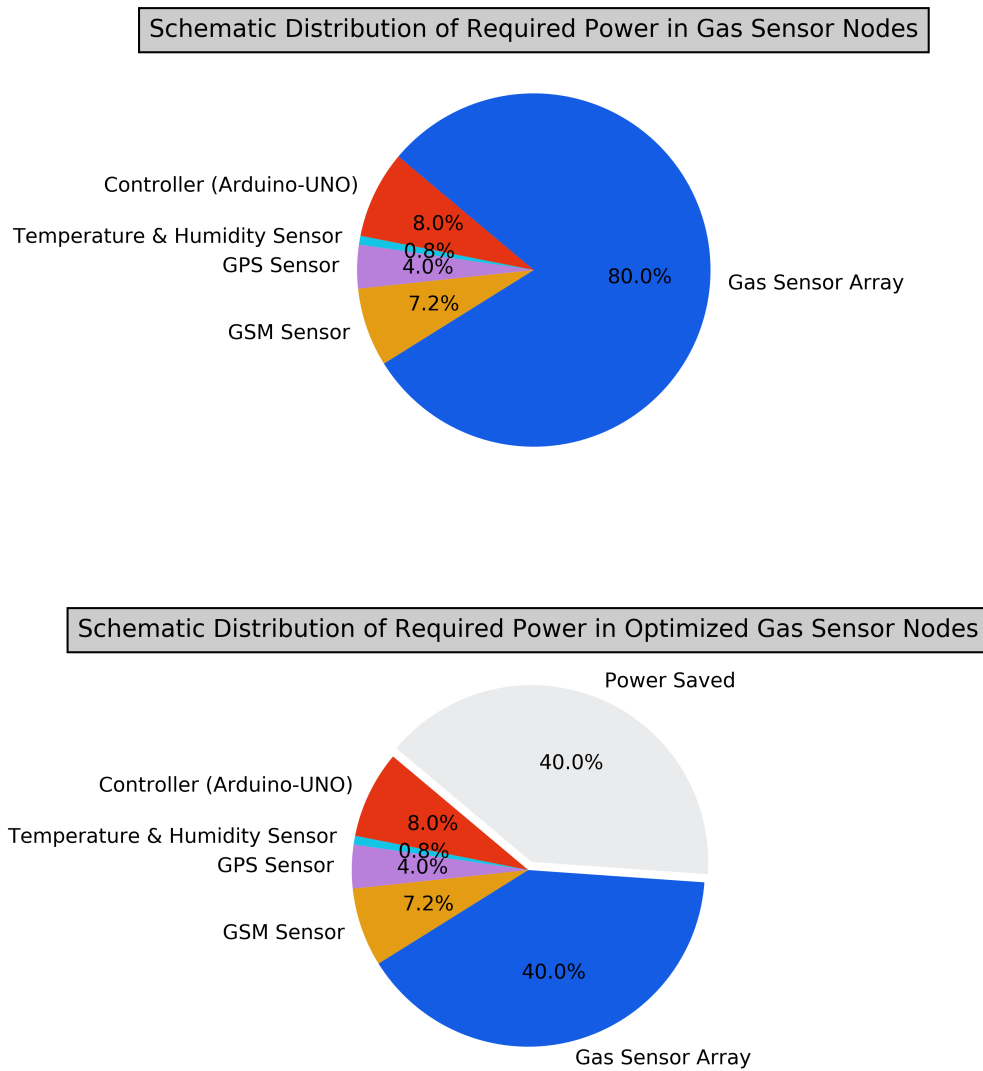


FIGURE 5.8: Approximated power requirement distribution in gas sensor node: (a) **UPPER**: before optimization, (b) **LOWER** after optimization.

nodes orienting towards portable and wearable sensor technologies. Each of the salient features of our approach, viz., power efficiency, less hardware, low cost, and the less complex architecture of the simpler 2D-CNN, makes it evidently suitable for resource-constrained 6G-IoT applications. Our work is the first application of 2D-CNN that utilizes steady-state responses to classify and quantify the considered gases/odors. In the data-constrained situations that occur due to the limited size of data vectors, padding and spatial augmentation may be the best techniques to overcome the issues of incompatibility of 2D-CNNs. Thus, the gas sensor systems developed using our approach can be conveniently designed in laboratory conditions. While supporting 6G-IoT in resource-constrained industrial and consumer sectors, it can deliver high performance in real-time applications.