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## An inexpensive sensor for noise

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### ABSTRACT

Noise is a pervasive workplace hazard that varies spatially and temporally. The cost of direct-reading instruments for noise hampers their use in a network. The objectives for this work were to: (1) develop an inexpensive noise sensor (<\$100) that measures A-weighted sound pressure levels within  $\pm 2$  dBA of a Type 2 sound level meter (SLM; ~\$1,800); and (2) evaluate 50 noise sensors for use in an inexpensive sensor network. The inexpensive noise sensor consists of an electret condenser microphone, an amplifier circuit, and a microcontroller with a small form factor (28 mm by 47 mm by 9 mm) than can be operated as a stand-alone unit. Laboratory tests were conducted to evaluate 50 of the new sensors at 5 sound levels: (1) ambient sound in a quiet office; (2) 3 pink noise test signals from 65–85 dBA in 10 dBA increments; and (3) 94 dBA using a SLM calibrator. Ninety-four percent of the noise sensors ( $n = 46$ ) were within  $\pm 2$  dBA of the SLM for sound levels from 65–94 dBA. As sound level increased, bias decreased, ranging from 18.3% in the quiet office to 0.48% at 94 dBA. Overall bias of the sensors was 0.83% across the 75 dBA to 94 dBA range. These sensors are available for a variety of uses and can be customized for many applications, including incorporation into a stationary sensor network for continuous monitoring of noise in manufacturing environments.

### KEYWORDS

Hazard; network sensor; noise; sound; sound pressure level

## Introduction

Each year, over 22 million workers in the United States experience occupational exposures to potentially hazardous sound levels.<sup>[1]</sup> Exposure to hazardous sound levels can result in disabling hearing loss.<sup>[2]</sup> Between 2003 and 2012, the prevalence of hearing loss across all industries approached 13%.<sup>[3]</sup> In order to protect worker hearing, the Occupational Safety and Health Administration (OSHA) sets a legally enforceable permissible exposure limit (PEL) of 90 decibels, A-weighted (dBA), as an 8-hr time weighted average (TWA).<sup>[4]</sup> Additionally, OSHA requires employers to implement a hearing conservation program when sound levels exceed an action level of 85 dBA TWA. The American Conference of Governmental Industrial Hygienists (ACGIH) recommends a more conservative threshold limit value (TLV) TWA of 85 dBA.

Traditionally, occupational noise exposure is measured with a dosimeter or a sound level meter (SLM). These instruments can cost up to \$2,000 USD. Dosimeters are affixed to the worker's collar and provide a percentage of the full noise dose experienced by the worker. Sound level

meters provide information on noise levels within an area and are primarily used for screening purposes to determine where dosimetry should be performed or to designate “high noise” areas. OSHA requires that sound level meters meet the American National Standards Institute Standard S1.4, “Specifications for Sound Level Meters,”<sup>[5]</sup> in which 3 different types of SLM performances are identified. Type 2 meters are most commonly used in occupational environments and have an accuracy of  $\pm 2$  dBA, the minimum to comply with the OSHA noise standard.<sup>[6]</sup>

An increasingly common way to visualize hazards in the workplace and determine their source is through the development of hazard maps. Hazard maps have been generated with handheld direct reading instruments,<sup>[7]</sup> a roving cart of direct reading instruments,<sup>[8]</sup> or a network of stationary sensors.<sup>[9]</sup> Uncertainties can arise when measuring sound levels by mobile mapping, especially concerning the temporal distribution of hazards.<sup>[10]</sup> A network of continuous stationary sensors is attractive because it continuously yields spatial and temporal knowledge of the hazard.<sup>[9]</sup> However, the price

of standard-compliant, direct reading instruments for sound, like a dosimeter or SLM, can severely limit the opportunity to collect simultaneous information from the many locations necessary to continuously monitor a workplace.

Developments in low-cost technology present opportunities to use inexpensive microphones, like electret condenser microphones, to measure sound pressure levels. A number of SLM applications (apps) are available for download onto personal smartphones. However, concerns have arisen to the applicability of these apps for occupational environments. Studies assessing the validity of these apps have found that the accuracy and precision is dependent upon the phone model and the software version.<sup>[11–14]</sup> The variability in performance of some apps may be improved with the installation of an external microphone, but this is not a viable solution for all phone types.<sup>[15]</sup>

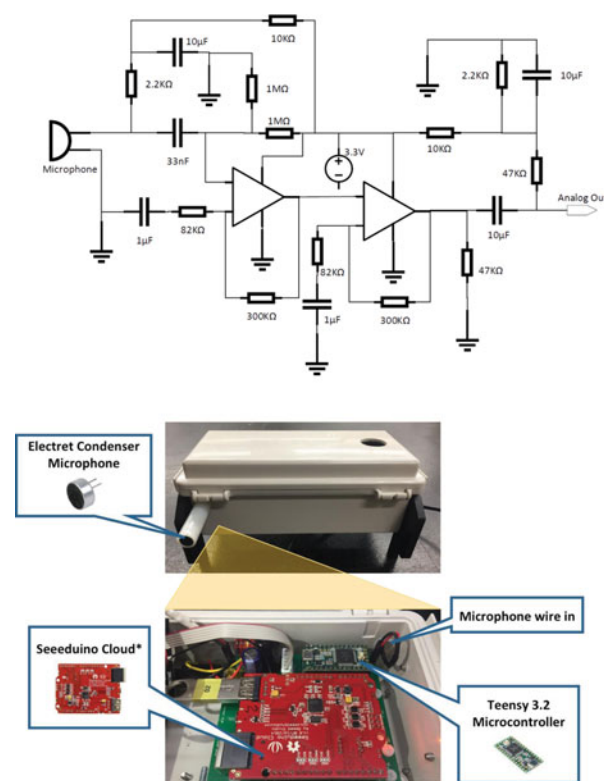
While the advancements in smartphone SLM apps are promising, there are a number of limitations to their use in a stationary sensor network. Roberts et al.<sup>[15]</sup> found an upper limit noise limit around 90 dBA on an app they evaluated. With the OSHA PEL for noise set at 90 dBA TWA, it is essential that a sound sensor designed for use in an occupational environment provide accurate sound level readings at levels near and above the PEL. The requirement of a smartphone and SLM app to gather data in each node of a network is impractical and dramatically raises the overall cost of a sensor network. Isolating the microphone and computational components of the SLM from the phone would allow for the use of this low-cost technology in a variety of different environments and for a variety of uses, like a stationary sensor network.

Thus, the primary objective of this work was to design a compact noise sensor that measures A-weighted sound levels within 2 decibels of a Type 2 reference SLM with components costing less than \$100 and independence from a smartphone. The second objective was to evaluate 50 of these sensors in a laboratory setting.

## Methods

### Sensor design

We developed a noise sensor for integration into a multiple hazard monitor with additional sensors for gases, aerosols, temperature, and relative humidity (Figure 1). These monitors have been incorporated into a sensor network to map multiple hazards in an occupational setting, specifically a heavy-vehicle manufacturing facility. Preliminary sound pressure levels in this facility were all greater than 65 dBA. Thus, we optimized the sensor



**Figure 1.** The inexpensive noise sensor. A simplified circuit diagram (top panel) shows that the electrical signal from the microphone is amplified twice before reaching the sensor microcontroller (Teensy). The actual components of noise sensor incorporated into multi-hazard monitor are shown in the bottom panel. An electret microphone extends from the exterior of the grey enclosure and the sensor microcontroller is shown inside the enclosure. On the red circuit board, a monitor microcontroller communicates with the noise and other hazard sensors and with a database via WiFi.

circuitry to measure sound levels between 60–95 dBA, 5 dBA above the OSHA PEL.

The noise sensor consists of a microphone, amplifier circuitry, and a sensor microcontroller with all parts costing less than \$30 retail. A 20 Hz to 20 kHz omnidirectional analog electret condenser microphone (CMA-4544PF-W, CUI Inc., Tualatin, OR, USA), housed at the end of a plastic tube, projects from the exterior of the monitor enclosure. The outer diameter of the tube was 12.7 mm (1/2 in) for compatibility with a standard acoustical calibrator (Figure 1). Analog voltage from the microphone passes through 2 amplifiers (MCP6022, Microchip Technology, Chandler, AZ, USA) in series (4.93x gain) and is then acquired by a sensor microcontroller (Teensy 3.2, PJRC, Sherwood, OR, USA), as shown in Figure 1. The sensor microcontroller samples 1024 amplified voltages ( $N$ ) over a 0.023 sec period ( $\Delta t$ ). The acquired sample voltages are then processed with Fast Fourier Transform (FFT) to a power spectrum with 512 frequency bins, ranging from 0–22.05 kHz to encompass the frequency range of human

hearing. The FFT code was developed using the Teensy Audio Library.<sup>[16]</sup> An A-weighting coefficient is then applied to each bin of the power spectrum to determine the A-weighted power spectrum ( $X_A$ ).<sup>[5]</sup> The A-weighted decibels for the sampling period is obtained by summing the A-weighted frequency spectrum as follows:<sup>[17]</sup>

Signal Level in dBA

$$= 10 \log_{10} \left( \frac{2}{N \Delta t} \sum_{k=0}^{\frac{N}{2}} |X_A[k]|^2 \right) + C, \quad (1)$$

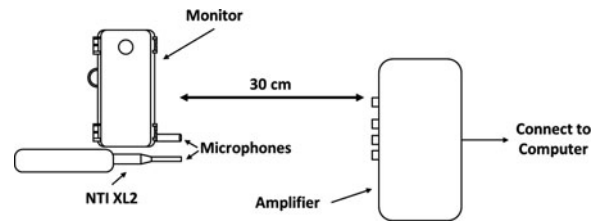
where C is a calibration constant.

The calibration constant was determined using a 1 kHz tone and side-by-side comparison of the sensor output with a Type 2 SLM (XL2 Audio and Acoustic Analyzer, NTi Audio, Tigard, OR, USA) and microphone (M4260, NTi Audio, Tigard, OR, USA). This SLM was selected because it was compatible with a previously developed data logging program. A sample of 3 noise sensors were evaluated to determine if the same calibration constant could be applied to all sensors. A calibration constant of 127.5 was applied to all sensors to adjust the A-weighted frequency spectrum to the signal level in dBA.

The noise sensor (microphone and sensor microcontroller) can be operated as a stand-alone device with a form factor of approximately 28 mm by 47 mm by 9 mm. In this work, we evaluated the noise sensor integrated into the multi-hazard monitor. Within the monitor, a program on the monitor microcontroller (Seeeduino Cloud, Seeed Development Limited, San Leandro, CA, USA) requests data from the sensor microcontroller once every 2.5 sec, triggering the sensor microcontroller to send the most recently calculated A-weighted decibel sound level. This 2.5 sec data can be accessed directly from the monitor by USB connection. For purposes of the sensor network, the monitor microcontroller collects the 2.5 sec data from the sensor microcontroller, averages, and then sends 5-min averages of the sound levels to a monitor database.

### Laboratory evaluation

The sound pressure levels measured with 50 noise sensors embedded within the larger monitors were compared to those measured with an SLM (XL2 Audio and Acoustic Analyzer, NTi Audio, Tigard, OR, USA) (Figure 2). Each noise sensor was tested individually inside a quiet office. The microphones of the SLM and noise sensor were placed within 2.5 cm of each other and 30 cm from the center of a guitar amplifier (Fender Musical Instruments Corporation, Frontman 10G, Scottsdale, AZ, USA). The amplifier was connected to a laptop computer with an auxiliary cord. Five target sound levels, ambient, 65 dBA, 75 dBA, 85 dBA, and 94 dBA, were generated to test each noise sensor. These sound levels were adapted from the



**Figure 2.** Setup for laboratory validation of noise sensor. NTi XL2 and noise sensor microphones were located within 2.5 cm of one another, centered 30 cm from the center of the amplifier. The amplifier was connected to the laptop by auxiliary cable.

range used by Kardous and Shaw in their evaluation of smartphone applications and to meet our needs to measure noise in a heavy-vehicle manufacturing facility. For levels from 65–85 dBA, pink noise was produced by playing a computer sound file (NTi Audio Test Signals for Audio and Acoustic Analyzers V1.0) through the guitar amplifier. The sound level was adjusted using the volume settings on the laptop and then verified on the reference SLM before each testing period began. The 94-dBA tone was generated using a sound level calibrator (General Tools & Instruments, SCAL1356, Secaucus, NJ, USA). Each test tone was generated for 30 sec before moving on to the next. Both the noise sensor and SLM reported 1 sound pressure level measurement every 2 sec over each 30-sec testing period,  $n = 50 \text{ sensors} \times 5 \text{ test levels} \times 1 \text{ measurement every 2 sec} \times 30 \text{ sec} = 3,750 \text{ paired measurements}$ .

The manufacturer stated performance range for the SLM and microphone is 29–144 dB with a resolution of 0.1 dB. The SLM used for laboratory comparison was newly purchased at the start of experiments and calibrated prior to each testing day with a 114 dB tone generated with a sound level meter calibrator (SCAL1356, General Tools & Instruments, Secaucus, NJ, USA). For all experiments, the SLM was programmed to report the A-weighted equivalent sound level ( $LA_{eq}$ ). No threshold sound level was designated in the SLM settings.

### Data analysis

For each sensor at each test level, we calculated the mean and standard deviation of the sound level reported by the sensor and the SLM. The difference between the means of the noise sensor and the SLM was compared to our acceptance criterion of  $\pm 2$  dBA. This criterion was adapted from ANSI standard S1.4 – 1983 (R2007) for Type 2 SLMs as an indication of accuracy.<sup>[5]</sup>

Further analyses were conducted on sensors passing this acceptance criterion. For test levels over all sensors, we calculated the mean and standard deviation of individual sensor means. At each test level as an indication of

sensor precision, we calculated the coefficient of variation as the standard deviation divided by the mean sound level reported by all sensors. As an indicator of accuracy, we calculated bias for each sensor and test level as difference in the sound level reported by the sensor and the SLM divided by that reported by the SLM.

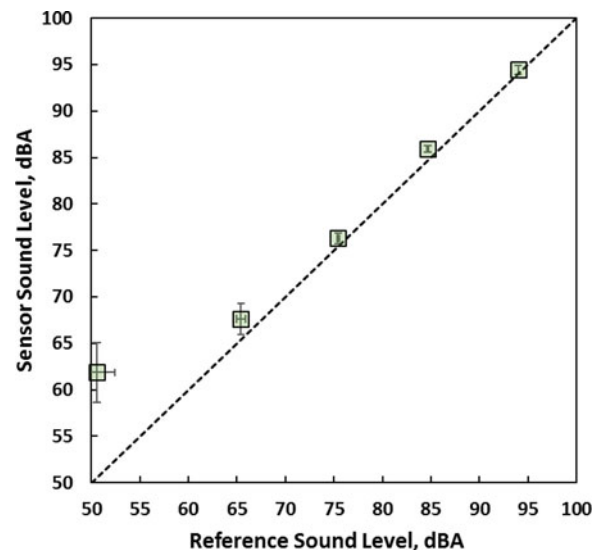
For each sensor, simple linear regression analysis was conducted to determine the slope, intercept, and coefficient of determination between the sensor and SLM outputs. We also determined the Pearson correlation coefficient. Overall statistical measures for coefficient of variation, bias, slope, and intercept were calculated as the mean of individual values over 2 ranges relevant to occupational environments (65–94 dBA and 75–94 dBA). Calculations were conducted using Microsoft Excel.

A paired sample t-test was conducted to test the hypothesis that the sound level measured by the new sensor was equivalent to that measured with the SLM at each testing level with an alpha of 0.05. Significant p-values indicate a difference in the mean of the noise sensor from the SLM. All t-tests were conducted on SAS (Cary, NC, USA).

## Results

Ninety-two percent of the noise sensors ( $n = 46$ ) passed our acceptance criterion of  $\pm 2$  dBA deviation from the SLM from 75–94 dBA. The noise sensors that did not meet criteria were removed from the monitor pool, repaired, and retested prior to field deployment. In this article, we report only on the results from the initially accepted sensors. Repair of the sensors involved trouble-shooting with replacement of a faulty microphone or circuit board. The use of a 94 dBA tone from a sound level calibrator was adequate to confirm proper functioning of the sensor.

The mean A-weighted sound level measurements of the noise sensor compared to the SLM are presented in Figure 3 and Table 1. At the ambient test level, the difference between the A-weighted sound level measured by the noise sensor and the SLM mean was nearly 12 dBA, the noise sensor over reporting. Although this difference



**Figure 3.** Mean A-weighted sound levels from noise sensor versus reference SLM at 5 target sound intensities. Points represent mean reading of all noise sensor and reference measurement pairs. Error bars represent one standard deviation of levels,  $n = 46$  sensors.

decreased as the sound pressure level increased, the mean measurement of the noise sensors was statistically different from that of the SLM at all testing levels ( $p < 0.05$ ). Variability in the measurements, as indicated by the standard deviation, decreased as the test level increased.

Mean percent bias at the target sound levels ranged from 18.3% at ambient to 0.48% at 94 dBA, with a monotonic decrease in bias as the sound pressure level increased (Table 1). Percent bias close to zero indicates only slight differences between the values reported by the inexpensive noise sensor and the SLM. The percentage of monitors that met acceptance criteria also increased as sound level increased. Very few of the noise sensors met acceptance criteria at ambient sound levels less than 60 dBA, whereas 100% of the monitors met acceptance criteria for 85 dBA and 94 dBA.

Overall performance statistics of the noise sensors across 2 different ranges of sound pressure levels (65–94 dBA and 75–94 dBA) are presented in Table 2. While the 95% confidence intervals for both slopes included unity, slope measures were improved in the more restricted

**Table 1.** Mean A-weighted sound levels, standard deviation, and coefficient of variation at 5 target dBA levels (side by side, 65, 75, 85, 94 dBA). P-values are resultant from one-sided t-test with an alpha of 0.05. Acceptance criteria is defined as monitor output within  $\pm 2$  dBA of reference output,  $n = 46$  monitors.

	Mean $\pm$ SD (dBA), CV (%)		Average bias, %	p-value	% within $\pm 2$ dBA
	Reference SLM	Sensor			
Ambient	50.6 $\pm$ 1.9, 3.8	62.0 $\pm$ 3.2, 5.2	18.3	<0.0001	2.1
65 dBA	65.4 $\pm$ 0.45, 0.69	67.7 $\pm$ 1.7, 2.4	3.22	<0.0001	62
75 dBA	75.4 $\pm$ 0.13, 0.18	76.3 $\pm$ 0.55, 0.72	1.15	<0.0001	98
85 dBA	85.2 $\pm$ 0.12, 0.13	85.9 $\pm$ 0.37, 0.43	0.83	<0.0001	100
94 dBA	94 $\pm$ 0, 0	94.4 $\pm$ 0.49, 0.52	0.48	<0.0001	100

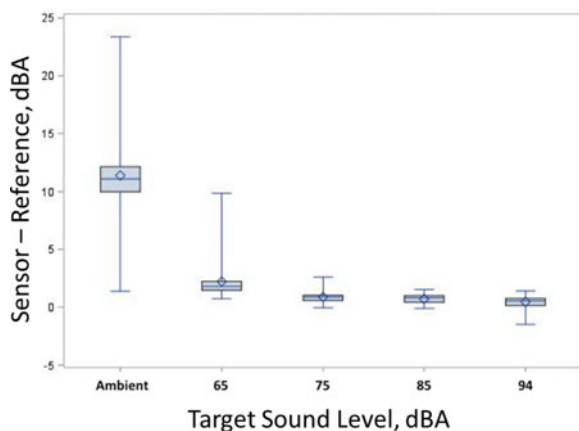


**Table 2.** Results of laboratory evaluation of noise sensors from 65–94 dBA and from 75–94 dBA,  $n = 46$  monitors.

		Mean	Std. dev	5 <sup>th</sup> percentile	95 <sup>th</sup> percentile
65–94 dBA	Slope	0.94	0.05	0.84	0.98
	Intercept, dBA	5.69	4.84	2.49	15.6
	Correlation, $r$	0.999	0.004	0.99	1.00
	Overall bias, %	1.47	0.77	—	—
	Overall CV, %	1.18	0.87	—	—
75–94 dBA	Slope	0.98	0.03	0.94	1.00
	Intercept, dBA	2.65	2.45	−0.41	6.67
	Correlation, $r$	0.999	0.001	1.00	1.00
	Overall bias, %	0.83	0.46	—	—
	Overall CV, %	0.76	0.27	—	—

75–94 dBA range ( $0.98 \pm 0.03$  dBA) compared to the 65–94 dBA range ( $0.94 \pm 0.05$  dBA). This result indicates that the noise sensor was in better agreement with the SLM at sound pressure levels greater than 75 dBA. The mean correlation between the sensor and SLM was slightly stronger from 75–94 dBA ( $0.999 \pm 0.001$ ) test range compared to the 65–94 dBA ( $0.999 \pm 0.004$ ) test range. The mean percent bias of the noise sensors improved from 1.47% to 0.83% when the 65-dBA testing level was excluded from the range. The mean coefficient of variation, CV, improved from 1.18% to 0.76% when the 65-dBA testing level was excluded from the range.

A box plot of the distributions of differences between the reference SLM and the noise sensor at each target testing level is presented in Figure 4. Differences between the output of the noise sensor and the reference SLM ranged from nearly 25 dBA at ambient sound levels to less than 2 dBA at the higher target sound levels. The range of differences decreased as sound level increased, similar to the trend observed in Figure 3. A difference of 0 between the sound level measured by the noise sensor and that measured with the SLM is indicative of agreement between the 2 devices.

**Figure 4.** Box plot of differences in noise sensor and reference SLM at 5 target sound levels. Error bars represent the distribution of A-weighted sound level differences,  $n = 46$  sensors.

## Discussion

The inexpensive noise sensor ( $\sim \$30$  for components) provided similar sound pressure level measurements in dBA to a substantially more expensive, Type 2 reference SLM ( $\sim \$1,800$ ) from 75–94 dBA. The stand-alone nature of the noise sensor developed in this work with embedded measurement and processing on-board, coupled with their small size and low cost, offers great potential for use in a variety of applications. Ninety-two percent of the noise sensors were within  $\pm 2$  dBA of the reference SLM from 65–94 dBA. This range encompasses the sound levels expected in manufacturing, for which the noise sensors were designed.

The accuracy of the noise sensors, represented as mean bias compared to the reference SLM, was 1.47% from 65–94 dBA. Bias was further reduced to 0.83% across 75–94 dBA. The bias determined in this study is equivalent to less than  $\pm 1$  dBA deviation from the SLM across the 75–94 dBA range. Kardous and Shaw<sup>[14]</sup> found similar accuracy for 2 SLM apps with the addition of an external microphone, SoundMeter, and SPL pro. Differences for these apps from the reference were between  $\pm 1$  dBA across the 65–95 dBA test range. SPLnFFT and Noisee apps had wider variations in sound pressure levels, especially at 65 dBA and 75 dBA.<sup>[14]</sup> Nast et al.<sup>[13]</sup> found a number of SLM apps that reported differences ranging from 3–10 dBA higher than the Type 1 SLM across their selected testing frequencies.

The reference SLM equipped with a Type 2 microphone has an allowable error of  $\pm 2$  dBA deviation from a Type 0 laboratory standard. The noise sensor designed in this study performed well compared to the Type 2 reference, but this reference may be off by 2 dBA from the actual sound level. Our sensor introduces additional uncertainty and bias (1.15% for sound levels greater than 65 dBA) that must be considered. While the designed noise sensor is not intended for use in determining compliance, if decisions were to be made regarding worker health a +4 dBA safeguard should be applied to the reported sound pressure level output to account for observed and allowable error in Type 2 SLMs. This

safeguard ensures that an underestimate of the sound pressure level is not made.

The sensor response at sound levels lower than 75 dBA was not consistently within our acceptance criterion. There was a large distribution in the differences between the sensor and SLM at ambient and 65 dBA target levels, as observed in Figure 4. As the sound level increased, the spread of the distribution of differences between the sensor and SLM output decreased. Preliminary measurements collected at the heavy-vehicle manufacturing facility that these sensors were designed for resulted in sound level measurements consistently greater than 75 dBA. Additionally, sound levels less than 80 dBA are not of primary concern when controlling for noise hazards that may cause noise-induced hearing loss. The sensors are within our acceptance criterion for the sound range they were customized for and perform similarly to the Type 2 SLM.

Modifications can be made to the sensor circuitry to allow for application in a variety of workplaces with differing sound levels. The circuitry of these sensors could be customized using high or low-pass filters to improve accuracy at the tail ends of the tested range. While sound levels less than 80 dBA are not a primary concern for noise exposure in the workplace, they may be relevant for other environments, such as patient care in a hospital. Additional refinement could be made to improve the accuracy over the entire 65–94 dBA range, or a custom range for a desired environment. Adjustments can be made to the sample period of the FFT to collect voltages according to the specifications for impulse, slow, and fast weighting. The selection of a higher quality microphone may help accurately measure sounds lower than 75 dBA.

While a number of accurate SLM apps have been identified, there are limitations to their deployment into the workplace for noise monitoring. The smartphone required to utilize the app can be expensive and bulky, posing cost and functionality challenges. Moreover, the SLM apps are computationally demanding, and require a great deal of battery power. Additionally, concerns have been raised regarding data privacy, accuracy over time, and data export and sharing.<sup>[13,14]</sup> Removing the noise sensor from the smartphone alleviates a number of the concerns associated with SLM apps and opens the door for application to other projects beyond a stationary monitor network. For instance, the small form factor offers potential for repackaging the device into a wearable, personal model. Additionally, the availability of FFT output enables access to data required to provide the end user with octave band information that may help identifying determinants of exposure rather than just sound level. Although incorporated into a multi-hazard monitor, the noise sensor components could stand alone with the addition of a power source and data storage capabilities.

The purpose of this inexpensive noise sensor is to provide reasonably accurate A-weighted sound level measurements in real-time so that an occupational health professional can collect more spatial and temporal information on sound levels in their facility. The importance of temporal and spatial resolution for the representativeness of hazard maps has been established, especially in non-homogenous workplaces.<sup>[9]</sup> A clearer understanding of the variations in sound levels throughout the facility and across shifts with a stationary monitor network will allow for better allocation of resources when conducting personal noise exposure measurements. However, the cost of SLMs has been prohibitive to the widespread applicability of a stationary monitor network. The noise sensor we evaluated met our previously stated objectives and is versatile for use in a variety of applications, like a stationary monitor network.

There were several limitations in this study. Testing of the noise sensors took place in a quiet office, not a reverberant chamber as other noise sensor testing studies have used.<sup>[12,14]</sup> Reverberant chambers create a diffuse sound field, removing the influence that positioning or reverberation off surfaces can have on the sound pressure level readings. In our study, the microphones of the noise sensor and reference SLM were setup close to each other to limit the influence of position and reverberation. The pink noise test signal selected for this study allowed insight into the sensor performance over a range of frequencies, but is not a perfect surrogate for real-world noise.<sup>[13]</sup> Additional evaluation of the sensor in an occupational environment should be conducted to account for differences in temperature, humidity, increased intermittent noise, and object interference—variables not present during the laboratory testing. These noise sensors are also not individually calibrated prior to use. The calibration offset, added on the sensor microcontroller during development of the sensor, improved accuracy of the sensors and allowed for consistent measurements of noise levels within 2 dBA of the reference SLM.

## Conclusions

A new, inexpensive noise sensor (~\$30 for components) developed in this work responded similarly to a substantially more expensive reference SLM from 75–94 dBA. The independence of this noise sensor from a smartphone, coupled with the small form factor and low price, allows for use in a variety of applications, including incorporation into a sensor network. Increasing the number of measurement points in a stationary network will improve the representativeness of hazard maps and better inform decisions on where further sampling should occur. Future work includes optimization of the noise sensor for different work environments, improvement of

the accuracy of the sound measurements across the target range, and field assessment of sensor performance over time.

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