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Pervasive environmental sensing for Industry 4.0 as an educational tool

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Abstract

The reduced cost of implementing pervasive industrial sensing networks enables universities to incorporate these tools in engineering curricula. They provide engineering students from increasingly computerized backgrounds, such as mechanical and automotive engineering, the opportunity to work alongside students from technical schools who bring different skill sets than what students may be used to, synthesize historical data, and drive the sensing system's physical system design and implementation. This paper outlines this convergent curriculum's initial implementation stage, including the wireless environmental sensing Internet of Things (IoT) network, focusing on laboratory environmental sensing. Students placing many sensors around the lab and on equipment generates a wealth of real-time and historical data for use in the classroom and provides them a tangible example of learning to measure the world around them. This setup parallels the current varied Industry 4.0 state of the manufacturing industry, where Big Data exists but is underutilized, and where additional sensors and intelligent machine data streams are added each year. Students in each class are given a defined portion of a broader roadmap to a fully instrumented and intelligent laboratory environment. In the first step, student-programmed environmental sensors were placed around the lab and provide temperature, humidity, pressure, and gas mixture measures every five minutes. Classroom use of the aggregated data includes visualizing the laboratory and essential equipment's current status using a Microsoft PowerBI dashboard and historical data visualization and analysis through trend forecasting and outlier detection in Python JupyterLab notebooks. The IoT system's installation also provided an infrastructure for further study of future student-designed IoT projects.

Keywords: Manufacturing Education; Pervasive Sensing; Engineering Education; Industry 4.0;

1. Introduction

Manufacturing education is evolving alongside the paradigm shift of industry 4.0. Traditional education domains are being blended in a convergent curriculum to meet these new job needs as modern manufacturing engineers become increasingly computerized with cross-domain knowledge expectations. Industry 4.0 encompasses the shift of disparate manufacturing systems to connected cyber-physical systems where heterogeneous data and knowledge are blended to achieve increased operational efficiency, productivity, and automation of tasks [1, 2]. U.S.A. education has shifted to a convergent problem-solving approach of blending expertise from multiple domains to provide more holistic education to meet these needs [3].

Two excellent examples of this shift are the work of Shih *et al.* and Summerville *et al.*.

Shih *et al.* used a quadcopter drone as a first-semester class culmination project in teaching undergraduate freshman an introduction to manufacturing, process planning and analysis, communication of one's ideas and with technical college students, the crossover of social sciences and manufacturing, and the basics of design for manufacturing to meet societal challenges [4]. Combining manufacturing and social sciences education provided freshman engineering students with an understanding of the interplay of manufacturing and design's significant impact on society and overcoming broader societal challenges.

Summerville *et al.* taught chemical engineers a design-oriented approach to manufacturing process selection during a four-day workshop on advancing chemical process innovations [5]. The workshop goals included instructing students in the Manufacturing Engineering discipline as a vehicle to translate laboratory technology through to commercialization. These skills are directly applicable to the current manufacturing shift to Industry 4.0 significantly increasing the required cross-domain knowledge. Surveyed participating students scored the manufacturing process portion of the workshop the highest with a high rating given to in-laboratory process demonstrations

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where students were able to see manufacturing processes in action for themselves.

Manufacturing is taught to a small subset of engineering students, primarily in the Mechanical and Industrial engineering tracks. At Clemson University in 2017, of the 24,387 enrolled students, only 5% (1331) of those were enrolled in mechanical or industrial engineering degree programs, while all engineering programs comprise 23% (5683) of enrolled students. At The Pennsylvania State University in 2017, of the 93,318 enrolled undergraduate and graduate students, only 2% (1716) of those enrolled in mechanical or industrial engineering degree programs, while all engineering programs comprised 14% (12960) of enrolled students. The percentage of students taught manufacturing as a required course is similarly mirrored at the University of Michigan in Ann Arbor. Of 6500 incoming first-year students in 2019, only 6% (400) were enrolled in degree programs with required manufacturing courses [4]. Students asked by Shih *et al.* in aerospace, chemical, and nuclear engineering responded that knowledge in manufacturing was essential to their domain and professional careers, yet opportunities for these students and especially non-engineering students, to have in-person or hands-on manufacturing experiences during their education are limited.

The numbers point towards a need to increase engineering students' opportunities and non-engineering students to be exposed to manufacturing education and how manufacturing is changing. The prior successes and student responses from Shih *et al.* and Summerville *et al.* also point towards including in-person experiences in manufacturing education curriculums which allow students to participate in manufacturing or at least to see the processes for themselves.

Unlike in the class examples presented, it was decided to focus the class solely on graduate-level students in the initial offering. This decision enabled the class's focus to execute a manufacturing context-based project rather than on teaching manufacturing concepts through in-person laboratory classes. Therefore, this class would be complimentary to the evolving manufacturing education programs. By diversifying the project group's background, students were pushed to discuss and teach each other concepts they had not encountered before but had been taught in their major or work experience.

1.1. Class Overview

The project-based class was an entirely new class offered through the Automotive Engineering department at Clemson University. It consisted of a semester-long effort going through project definition and planning, background research, self-setting measurable goals, evaluating software and hardware tools, prototyping a solution, and reporting conclusions. The problem statement given to the team was left intentionally open and ambiguous to allow them an opportunity to define the path they took and measures of success for the project, much as they will encounter during their professional careers. Students completed detailed reports and presentations of their work throughout to build communication skills. They were encouraged to learn new skills such as programming C-based micro-controllers, designing/building physical prototypes, and data visualization for a target audience that did not include them or their peers.

Students met weekly, first in the classroom and then moved to the laboratory and were free to use all facilities outside of classroom hours. The classroom activities included project updates, discussion of project activities, difficulties, and needs.

The four student team in the initial offering of the class were selected from the Clemson Technology-Human Integrated Knowledge Education and Research (THINKER) National Science Foundation (N.S.F.) Research Traineeship program, which is a graduate traineeship program supported by the N.S.F. where participating students in engineering graduate programs (including automotive, mechanical, industrial, human factors and computing) study collaboration, manufacturing, human behavior, and big data analysis along with special workshops in career education and planning. Lessons learned from the class's initial offering are being incorporated into an existing general mixed undergraduate/graduate automotive engineering class, Digital Manufacturing, to be offered in 2021.

To assist in the development of new or altered courses, the Clemson University Vehicle Assembly Center (CVAC) at the Greenville Technical College Center for Manufacturing Innovation is working with students from multiple engineering degree programs and with technical school students to complete multi-domain hands-on projects to simulate the types of projects that the students will work on in their careers. CVAC represents an opportunity to reimagine approaches to automotive assembly and engineer, technician, and operator education. CVAC comprises a three-station automotive assembly skid line with a vehicle body, raised static assembly platform, dedicated enterprise server and data network, and controlled environmental abilities such as high-fidelity background noise. The laboratory mimics the current automotive assembly environment while providing a controlled space for student and industry prototyping and research activities.

As a step in developing the space's cyberinfrastructure, an Industrial Internet of Things (IIoT) network was deployed by students placing wireless sensors throughout CVAC to monitor environmental and worker health conditions. Students defined the metrics to be monitored, including air quality, temperature, pressure, and humidity, and these data were to be used to evaluate worker comfort and safety. These monitoring outputs were displayed on a user-friendly dashboard to assist production management (laboratory personnel) in decision-making and planning. Collected data were aggregated and will be analyzed via future student projects in machine learning to classify optimal and sub-optimal conditions, control strategies, and sensor fusion as additional sensors and data streams are incorporated.

2. Project

Students were given the problem of indoor air quality in manufacturing and tasked with identifying applicable metrics, defining the physical sensors that would be needed, data analy-

Table 1. Major indoor air pollutants and emission sources adapted from [6]

Pollutant	Major Emission Source
Allergens	House dust, domestic animals, insects
Asbestos	Fire retardant materials, insulation
Carbon dioxide	Metabolic activity, combustion activities, motor vehicles in garages
Carbon monoxide	Fuel burning, boilers, stoves, gas or kerosene heaters, tobacco smoke
Formaldehyde	Particleboard, insulation, furnishings
Micro-organisms	People, animals, plants, air conditioning systems
Nitrogen dioxide	Outdoor air, fuel burning, motor vehicles in garages
Organic substances	Adhesives, solvents, building materials, volatilization, combustion, paints, tobacco smoke
Ozone	Photochemical reactions
Particles	Re-suspension, tobacco smoke, combustion products
Polycyclic aromatic hydrocarbons	Fuel combustion, tobacco smoke
Pollens	Outdoor air, tress, grass, weeks, plants
Radon	Soil, building construction materials (concrete, stone)
Fungal spores	Soil, plants, foodstuffs, internal surfaces
Sulphur dioxide	Outdoor air, fuel combustion

sis methods, and providing a visualization intended for a mixed knowledge background audience. The following section includes sources and information that the student team found necessary in building the case for implementing sensors in a factory and office environment, a description of the system design, and resulting data visualization. Due to Spring 2020 COVID-19 restrictions and university cancellations, the student team could not implement their entire project plan, but a section on additional sensors that the student team identified as important and plans for visualization are included.

2.1. The problem of indoor air quality

The majority of the average U.S. person's day is spent indoors. A 2001 National Human Activity Pattern Survey in connection with the U.S. Environmental Protection Agency National Exposure Research Lab found that, on average, respondents spent 87% of their time in enclosed buildings and 6% of their time in enclosed vehicles [7]. Much work has been directed to understanding the effect of indoor air quality on health as changes in building materials has resulted in higher energy efficiency and lower cost structures that are more airtight and made with higher percentages of synthetic materials [8]. These improvements have produced more comfortable homes and offices while also allowing for the buildup of higher concentrations of indoor air pollutants. Office productivity losses due to air quality have been found to be between 6% and 9% [9]. Indoor air pollutants come from many sources, such as those presented in Table 1. The origins of pollutants are both biological and non-biological, and many are the emissions from activities within the building. Combustion of fuel to emissions from building materials, furniture, foodstuffs, and people, there is a constant source for indoor air pollutants.

Historically, measuring the amount of exposure to indoor air pollution has been difficult or impossible as most measurement tools were developed for outdoor usage or were too costly to deploy on a large and continuous scale [8]. Advances in sensor technology and significantly reduced cost of sensors, and associated computing have made small, low-cost sensors available to businesses and individual consumers. The second gap in current practices is that most deployed sensors developed for indoor usage record and average over many hours, days, or weeks potentially missing extreme short-term exposure. A third gap is that the density of the deployed sensors is extremely low. In an example 4,000 square foot (100 ft x 40 ft) office space, there are typically one or two thermostats mounted on the wall to measure and control the temperature for the entire area. With two points of reference for the measurement, if one thermostat reads higher than the set point for a time, due to an increased number of occupants gathering to talk or a computer or printer emitting significant heat, the entire 4000 square foot space will be cooled to reduce the temperature in the localized zone. From these gaps, a denser grid of continuously monitoring sensors has the potential to improve indoor air quality and improve building efficiency by using data to generate knowledge.

2.2. Pervasive environmental sensing

A brief background is presented to establish the real-world significance of necessary environmental measures for understanding while in the classroom and actively monitoring health conditions by the students later in industry.

Temperature and humidity are the most commonly referenced measurements used when describing weather and environmentally based worker comfort. Research has shown that productivity falls when temperatures are too high [10]. High temperature and humidity can also increase a worker's chance of having a heat-related illness. This is reason enough to track these measures, but temperature and humidity also play a role in machine function and maintenance needs. As the sensors will be placed in more locations than the current thermostats, we will get a better picture of what is occurring in distinct areas. Suppose the temperature in a specific area of the lab is considerably higher than the day before. In that case, it may be caused by outdoor environmental conditions affecting indoor conditions, by a machine malfunction causing excess heat to be produced, or by students leaving lab equipment running overnight. Without an understanding of the change's evolution (the collected data), it may be more challenging to diagnose the root cause (knowledge generation).

Gas monitoring, such as for carbon monoxide, has been prevalently monitored in indoor spaces due to known safety concerns. As increased focus has been placed on indoor air quality, additional compounds have been monitored on a one-time per year manual check or long-term time-averaged basis that may not provide the full exposure history for an occupant [11]. Additional compounds such as benzene, toluene, xylenes, styrene, formaldehyde, terpenes, and ammonia, to name a few, have become of interest due to their increased usage in commercial and consumer products. Compounds such as formaldehyde and benzene are generally regarded as carcinogenic, meaning exposure above allowable thresholds or length of time poses a demonstrated health risk [6, 11]. Toluene, xylenes, styrene, terpenes, and ammonia are generally regarded as non-carcinogenic but have the potential to cause eye and respiratory irritation, dizziness, headaches, or bronchitis at higher concentrations [11, 12]. Monitoring air quality for these contaminants may help detect and mitigate worker exposure.

2.3. Additional student identified sensors

Additional worker well-being factors that the students could not implement included the manufacturing environment's noise level and the worker's mental workload. Internationally, occupational noise exposure causes between 7% and 21% of the hearing loss among workers in industrial settings [13]. The National Institute for Occupational Safety and Health has set recommended exposure limits for sound to protect workers against permanent hearing loss [14]. The daily exposure limits are shown below in Table 2 and can serve as guidelines for monitoring "good" and "bad" durations of noise exposure.

Table 2. NIOSH Average Sound Exposure Levels Needed to Reach the Maximum Allowable Daily Dose of 100%

Time to reach 100% noise dose	Exposure level per NIOSH REL
8 hours	85 dB(A)
4 hours	88 dB(A)
2 hours	91 dB(A)
60 minutes	94 dB(A)
30 minutes	97 dB(A)
15 minutes	100 dB(A)

Worker well-being may be affected by factors relating to mental workload. Many different factors have been shown to correlate with increases in mental workload, and these increases have been shown to affect performance [15]. These factors can be represented by physiological responses to increased cognitive processing or stress-related responses. In general, monitoring mental workload aspects is most effectively done by assessing several triangulating variables simultaneously [16]. These

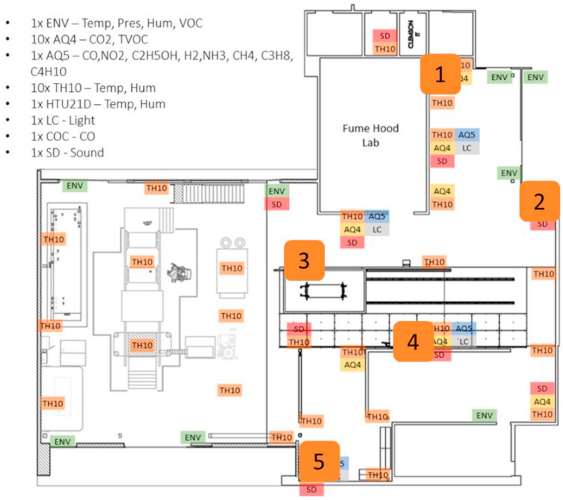

Fig. 1. Proposed student prototype sensor locations in laboratory space listed by sensor designation and location, actual locations marked with numbers 1-5

responses can increase workers' ease of tasks or indicate when a particular employee may need a break.

While many different physiological responses exist for measuring cognitive workload, a few of the most common are heart rate variability, galvanic skin response, and signals from electroencephalogram (E.E.G.) headsets [17]. For student analysis, heart rate variability was chosen as the primary method of monitoring operator workload due to its ease of collection through wearable devices and the broad literature base of use cases. Heart rate variability as a measure for assessing an individual's cognitive workload is a form of indirect measurement that has been shown to correlate with cognitive activity closely. Studies have shown that, in addition to assessing physical workload, this simple measurement has been used to indicate higher levels of mental stress in subjects based on their working environment [18].

2.4. System Design

The Clemson Vehicle Assembly Center (CVAC) is a large space with three separate labs cohabitating one space. To better cover the space than the existing two wall-mounted thermostats, the students were asked to propose enough sensor locations and types to cover the laboratory space's entirety. Thirty-six separate sensor locations, as in Figure 1, were selected to target. The locations were selected to spread the sensor points around so that a reasonable interpolation could be completed, hot spots identified, and source location approximated. Locations included placing sensors near high traffic areas, near doorways, or significant equipment (example, a heat and gas generating composite extrusion machine). Each door to the CVAC included a pressure sensor to detect the doors' opening and closing throughout the day. One sensor location was placed outside under cover and out of direct sunlight to measure and compare internal conditions against external conditions. The number of locations and sensor types was then reduced in this initial deployment to demonstrate a proof of concept system. For this first phase, five locations were instrumented to be the pilot locations and can be found numbered in Figure 1.

Before selecting the individual sensors, the desired environmental information was determined by examining existing literature and governmental regulatory agency recommendations for Indoor Air Quality (IAQ). From these sources, the students determined that in this initial pilot, the system should target:

- Temperature
- Pressure
- Humidity
- Carbon monoxide (CO)
- Carbon dioxide (CO_2)
- Volatile Organic Compounds (VOC)
  - Nitrogen dioxide (NO_2)
  - Ethanol (C_2H_5OH)
  - Hydrogen (H_2)
  - Ammonia (NH_3)
  - Methane (CH_4)
  - Propane (C_3H_8)
  - Isobutane ($C_4H_1$0)
- Light Level

The sensors listed in Table 3 were selected to target each of the desired sensor streams from the list of data targets. To meet their goals, some areas included multiple sensors with similar data output.

2.5. Hardware

The BME680 is the primary sensor the team selected for measuring temperature and humidity. It can measure the relative humidity in the range from 0-100% and temperature in the range from –30 - +100 degrees Celsius, with an accuracy of plus or minus 3% humidity and plus or minus 0.4 degrees Celsius. The sensor requires relatively little power and is well suited to battery-powered applications. Another sensor that was considered is the HTU21D. It measures the same range as the BME680 for humidity, but it measures from –40 to +125 degrees Celsius in temperature. However, the additional range is unlikely to be needed when measuring the air temperature in the CVAC laboratory, but it may be needed in other production contexts. The sensor was sampled every 5 minutes to increase time-series resolution during the trial and artificially increase the growth of the database for performance testing.

A 13.5x13.5 cm A.B.S. enclosure, seen in Figure 2 was selected to enclose and protect each sensor and allow for ample room to mount the microprocessor, sensors, battery, and antenna with additional room if the battery size needs to be expanded in later revisions.

Each of the five pilot boxes was configured with a BME680, microcontroller, Mioty transceiver, and battery. Each box was powered by a rechargeable 3.7V 2000 mAh LiPo battery. The data is collected by an STM32F407VG Microprocessor, which includes an A.R.M. 32-bit Cortex-M4 CPU at 140 MHz and programmed in C through MikroC Pro for A.R.M. All compo-

Fig. 2. Prototype sensor box made by student team

nents run on either a Serial Peripheral Interface (S.P.I.) or Inter-Integrated Circuit (I2C) interface and are 3.3V tolerant to function correctly with the microprocessor. Current work with the system includes evaluating battery life per sensor type and collection frequency, whether a battery size change is required, and how long the sensor boxes will last between charges. Charging is completed through a mini-USB port on the microprocessor board and can be recharged through a standard USB 5V charger.

Data transmission is handled wirelessly using Behrtech Mioty MYTHINGS modules with an omnidirectional antenna and a single base station. Mioty is a 915 MHz telegram splitting Low Power Wireless Area Network (LPWAN) designed to be robust to high interference areas, ultra-low power consumption, and long transmission range. It is limited in the amount of data that can be transferred at one time, but as the application here includes sample rates that sample at a maximum of once per five minutes, this was not seen as impacting the system performance. An outline from Behrtech of the MYTHINGS data receiving and storage method is presented in Figure 3 for reference.

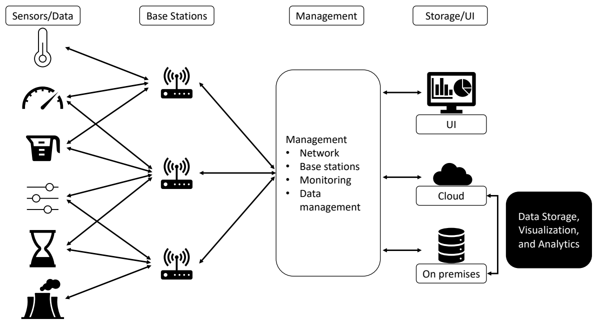

Fig. 3. Mioty data transmission outline. Expanded figure available in Appendix A

The A.B.S. enclosures were tough and water-resistant as received, so they were machined on a HAAS VF-3 to mill openings for environmental air to flow through them. The students were guided through the setup and use of the mill by a student lab leader. Additional miscellaneous components needed are 10mm M2 standoffs for mounting the microprocessor and sensors to the case, small command strips for holding the battery in place with the intention to replace it with a 3D printed mount in the future, and large command strips for holding the

Table 3. Sensor designation and data output

Sensor	Designation	Output
BME680	ENV	Temp., Pres., Hum., VOC
SGP30	AQ4	CO_2, TVOC
MiCS-6814	AQ5	CO, NO_2, C_2H_5OH,H_2,NH_3, CH_4 , C_3H_8, C_4H_10
BPS230	TH10	Temp., Hum.
MQ-7	COC	CO
Photocell	LC	Light
MEMS Microphone	SD	Sound level

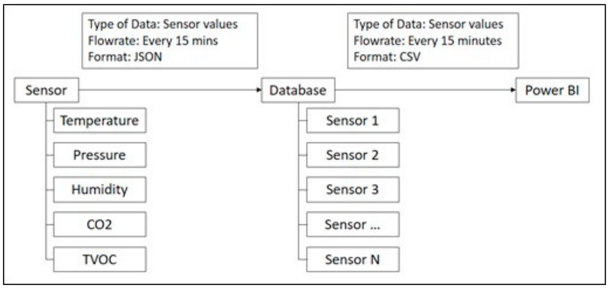

Fig. 4. Outline of data flow through system

boxes in place at their location. Command strips were used for mounting to allow for adjustment and movement of the boxes as desired without damaging the CVAC facilities.

It was right before this stage of work on the physical system that restrictions canceled in-person activities out of an abundance of caution for student safety. The next portion describes how the students would have completed the project based on their original project plan, as due to the restrictions, only portions of the following were able to be completed.

Data is collected on a timer, packaged into a (JavaScript Object Notation) JSON format message, and sent wirelessly to the base stations for ingestion and buffering. The data is then validated to contain the required information in an expected format without errors before being sent by NODE-RED to the CVAC server, where it is stored in a MySQL database. Each sensor has its own table to store information in columns for each of the timestamp and sensor streams.

The data is not altered from the collected form. Any calculated columns will be populated only in new columns, so the initially collected data is preserved. Additionally, a system health monitoring script will be written for the base station to monitor for missing data messages or sensor boxes in case of a sensor software fault, power running out, or physical damage. Each sensor entry increased the database size by approximately 1 K.B., but this is highly variable depending on the number of columns from both raw sensor reading, calculated value columns, and configuration of the MySQL database itself. In this system, which includes 5 sensors collecting every 5 minutes and including calculated columns, the database per year is estimated to grow by approximately 530 GB which is reasonably sized to be stored on a standard desktop P.C. using a spinning disk hard drive. Once stored in the server database, it will be pulled as needed by the central dashboard running through Microsoft Power B.I. on a computer for display on the laboratory's large screen. Any analytics or computation needed for display will be completed through the Power B.I. interface.

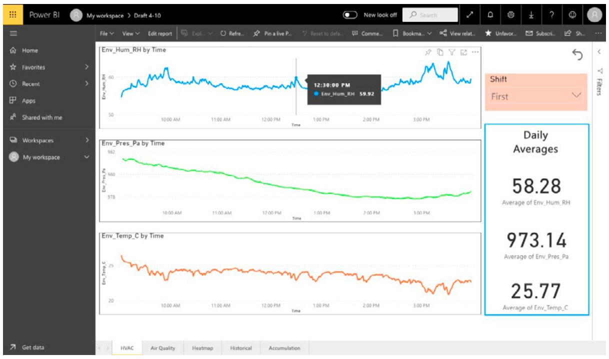

Fig. 5. PowerBI based visualization of temperature, pressure, and humidity for one sensor output. Full page figure available in Appendix B

As previously mentioned, once the data is sent to the central server, it is stored in a MySQL database. This database's schema may change based on the sensors used, but its generalized design is constant. Each sensor has been given its own table, as shown by Figure 4. The sensor tables must contain the timestamp and 'boxID' and the sensor measurements. A single relational table contains all of the 'boxID's with their physical locations and other metadata that the user may want. This method allows data to be queried based on the box, time, or sensor.

Although social distancing modifications affected the volume and representative nature of the data collected being from a house rather than the laboratory, a dashboard was still compiled for a visualization "proof of concept". The dashboard was designed in Power B.I. and is comprised of three main tabs: HVAC, Air Quality, and an exploratory Heatmap visualization. In general, the tabs specified below had three aims:

- To allow the user to view metrics over a useful window of time (e.g. three shifts)
- To quickly provide the user with summary statistics (e.g. daily averages)
- To display variations among the metrics in different areas of the facility (e.g. heatmap)

The first tab, titled “HVAC” and shown in Figure 5, captured data for quantities relevant to the performance of climate control equipment, which may also affect manufacturing processes and maintenance schedules. These quantities included air humidity (‘Env_Hum_RH’) in units of percent relative humidity, air pressure (‘Env_Pres_Pa’) in Pascals, and air temperature (‘Env_Temp_C’) in degrees Celsius.

The second tab, titled “Air Quality” and shown in 6, captures data relevant to the safety and quality of air in the environment. The three measures on this tab were carbon dioxide levels (‘CCS_CO2_ppm’) measured in parts per million, levels of volatile organic compounds in air (‘CCS_TVOC_ppb’) in parts per billion, and the concentration of gas in air (‘Env_Gas_KOhms’) which provides a variable resistance in Ohms.

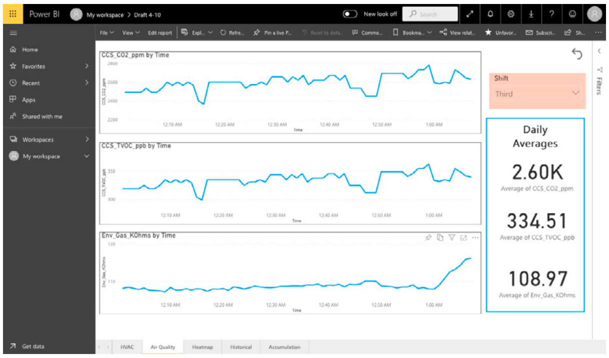

Fig. 6. PowerBI based visualization of air quality for one sensor output. Full page figure available in Appendix C

The third tab, titled “Heatmap” and shown in Figure 7, enabled the user to view certain metrics by specific physical area. This visualization could be overlaid on a schematic of CVAC and provided a spatially-representative view of the data coming from the sensors. The intention was to expand this to a smooth interpolated view based on multiple sensor outputs. Unfortunately, since the team could not use the sensors to measure the laboratory, the heatmap shown used “dummy data” as a proof of concept.

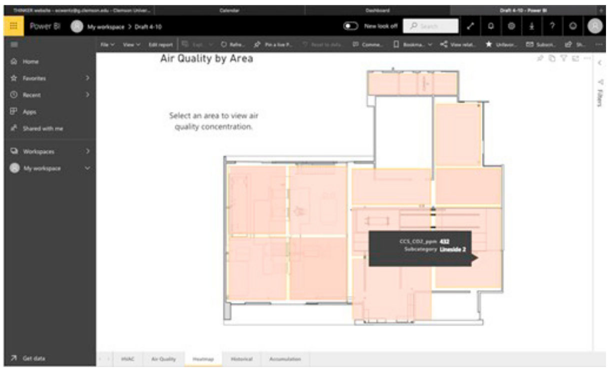

Fig. 7. PowerBI based visualization of interpolated distribution of air quality throughout laboratory space

The students explored two additional tabs and focused on historical data and the accumulation of exposure. A prolonged data collection was needed to use these visualizations fully but was limited by social distancing restrictions. The first tab included a “slicer” which allowed the user to view data over the past day, week, month, quarter, or year, for a selected shift or combination of shifts. The visualization shown in Figure 8 showed the historical distribution of CO2 levels.

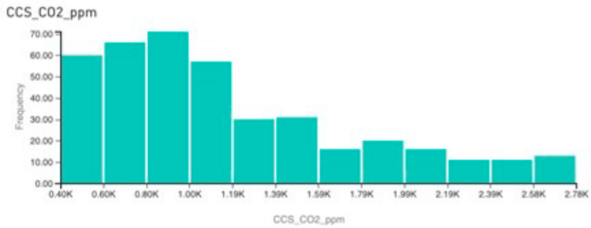

Fig. 8. PowerBI based visualization of historical distribution of air quality

3. Results and discussion

The initial project team consisted of graduate engineering majors from four departments. Two students were in the final semester of M.S. programs, and two were on Ph.D. programs. All were domestic U.S.A. students and came from varied undergraduate and graduate backgrounds in Mechanical, Industrial, Computing, and Automotive engineering programs. Tailoring a manufacturing project class for graduate students is in contrast to other literature that focuses primarily on undergraduate students. This provided the opportunity to focus less on teaching the skills of manufacturing itself and focus more on allowing students to use their skills while allowing them to determine what skills they needed to be taught. By the end of the course, students had opportunities to learn new skills in physical prototyping, including guided use of a 3-axis C.N.C. mill and hand tools, C programming, project management and goal setting, experience working with team members from varied backgrounds and knowledge, presentation of ideas, and dealing with initial ambiguity in a project definition.

Students were graded primarily on submitting deliverables that they defined early on in the semester, with project reports and presentations being the few required submissions from the start. The students had direct input in defining how they would be graded during their project goal-setting phase. Grades for project submissions included how thoroughly and clearly the ideas and meaning of the reports were conveyed.

Overall, the initial team worked well together and provided positive and constructive feedback. The students preferred that the project’s context was a production simulation environment that they could work in and walkthrough. There were mixed reactions to the ambiguity in the initial project problem statement and prompt. They recommended reducing the ambiguity and increasing the emphasis on explaining that the students would define the project’s goals and output as initially, the project’s scope was inferred to be much larger than it had to be. Reducing the initial ambiguity in terms of project tasks and specific deliverables will be considered during future class offerings. However, some level of ambiguity is needed to allow the students freedom to define their path to success and provides the opportunity to learn to manage uncertainty. The students also indicated a preference for increasing the amount of mid-term feedback. The feedback that the students received was in the context of graded presentations and written reports on progress. All students liked the hands-on prototyping activities, and they requested to increase the opportunity for in-person practical skill-building.

The data that is generated by the sensors are stored for future classes. In keeping with the hands-on nature of the project, the collected data provides a more tangible learning dataset for future coursework in machine learning and A.I. as the topics are more deeply integrated into the curriculum, where for example, students can increase or decrease consumption of additional power, air, or water and model the consumption fluctuation. As projects are completed, the number of sensors, diversity of sensor type, and calculated metrics will increase to improve the historical and real-time information available continually. Students were also asked to compile how-to guides and document difficulties that they encountered while completing the projects. While semi-formal in structure and content, this information is useful to future students who may use the same hardware/software or encounter similar difficulties that their group must overcome.

3.1. Remote learning in a laboratory-based class

Due to COVID-19 affecting all in-person classes at Clemson University partway into the semester, the students had to rapidly alter their project plan mid-semester and move to an all-online laboratory format. The flexible nature of the class format, allowing the students to define the end goals themselves, provided them with the ability to reasonably alter their project plan. The students reacted well and demonstrated flexibility and adaptability to alter their project outcomes while still satisfying the course's requirements. The students reduced their output scope but included a detailed plan for meeting the original goals, similar to what their future employer might expect when faced with significant negative external factors. Out of concern for student safety and keeping with university policy, all in-person laboratory activities were canceled, which meant that physical prototyping ended prematurely, and in-laboratory data collection had to be canceled. The students were able to continue their work from home and completed a prototype of their design with parts they had on hand and demonstrated how the system would have worked.

4. Conclusion

This work details a project-based graduate manufacturing class that provides in-laboratory opportunities for students to work with a multi-disciplinary team to meet a topical manufacturing need. The manufacturing need will change each semester and in partnership with local manufacturers. Overall, students had positive reviews of the class and format and provided valuable feedback to evolve the course further.

4.1. Future Development

Future sections of the class will be offered in a phased approach. A multi-phased approach is being used to ensure that student feedback is incorporated into subsequent projects, to ensure that each student is provided proper learning resources/outcomes based on their knowledge background and that the generalized project framework and requirements are sufficiently developed to provide for the best outcome. The work detailed here comprises the first phase. The second phase expands the class to include both graduate engineering and senior mechatronic community college students. A third phase will further expand the class offering to three or more groups and open enrollment for undergraduate and non-engineering majors. The output from phase three also includes a generalized project framework and requirements definition to facilitate an industrial partner project that needs translation for student projects.

The second phase offering of this class will continue in January 2021, as possible, and is open to two student teams of four graduate students each. It is intended to increase the opportunities to work with P.L.C. systems and the larger mechanical equipment and robotic systems available at the Clemson Vehicle Assembly Center. The second class iteration will be offered in partnership with the Mechatronic program offered by Greenville Technical College, which includes final year students to increase student background and knowledge diversity through their practical skills and more in-depth knowledge of mechanical equipment and control systems. Bringing both sides together has the intention that they are not only learners but also internal mentors for their group.

Augmenting the project to include tasks for both sides include adding additional sensing modalities such as collecting data from lineside P.L.C. systems, industrial sensor devices (example, proximity, temperature, vibration, distance, and safety), and incorporating new industrial sensor devices into the larger mechanical systems of vehicle lifts, drive motors, and surrounding infrastructure. Project supplies will also be augmented to provide the teams access to P.L.C. systems, such as a Siemens S7-1200 PLC with analog and digital input and output, and industrial sensing systems, such as I.F.M. Electronic GMBH VSE002 diagnostic module and VSA001 single-axis accelerometer. These devices were selected based on input from an industrial partner who is working to deploy and scale their Industry 4.0 sensing strategy. Similar to this work providing hands-on experience for graduate students, the next phase project aims to provide technical college students the opportunity to work with technology that they otherwise would not have had access to and that they will encounter during their career.

A future third phase class aims to offer undergraduate and non-engineering student opportunities while also increasing the number of teams. It is not expected that the project class will need to be altered significantly for undergraduate engineering students as many of the skills and expectations for graduate students are already on the edge or outside of the current curriculum. Students from non-engineering domains are not expected to significantly alter the desired learning outcomes, but their learning path will need to be tailored based on their background and in collaboration with their department.

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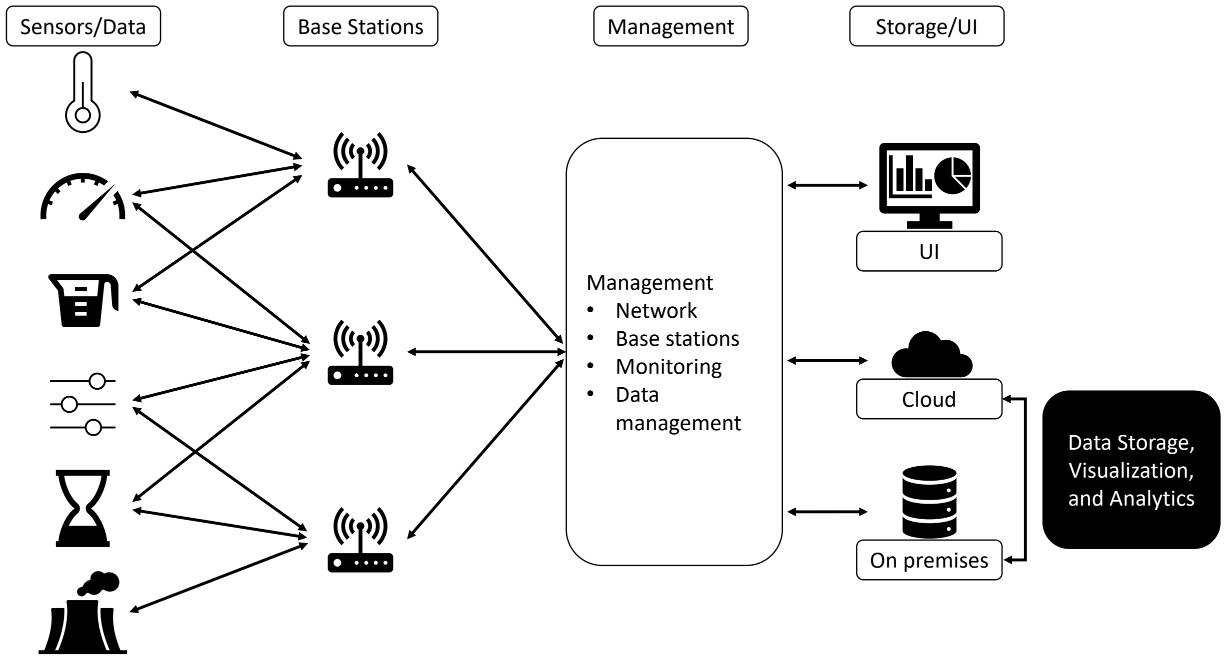
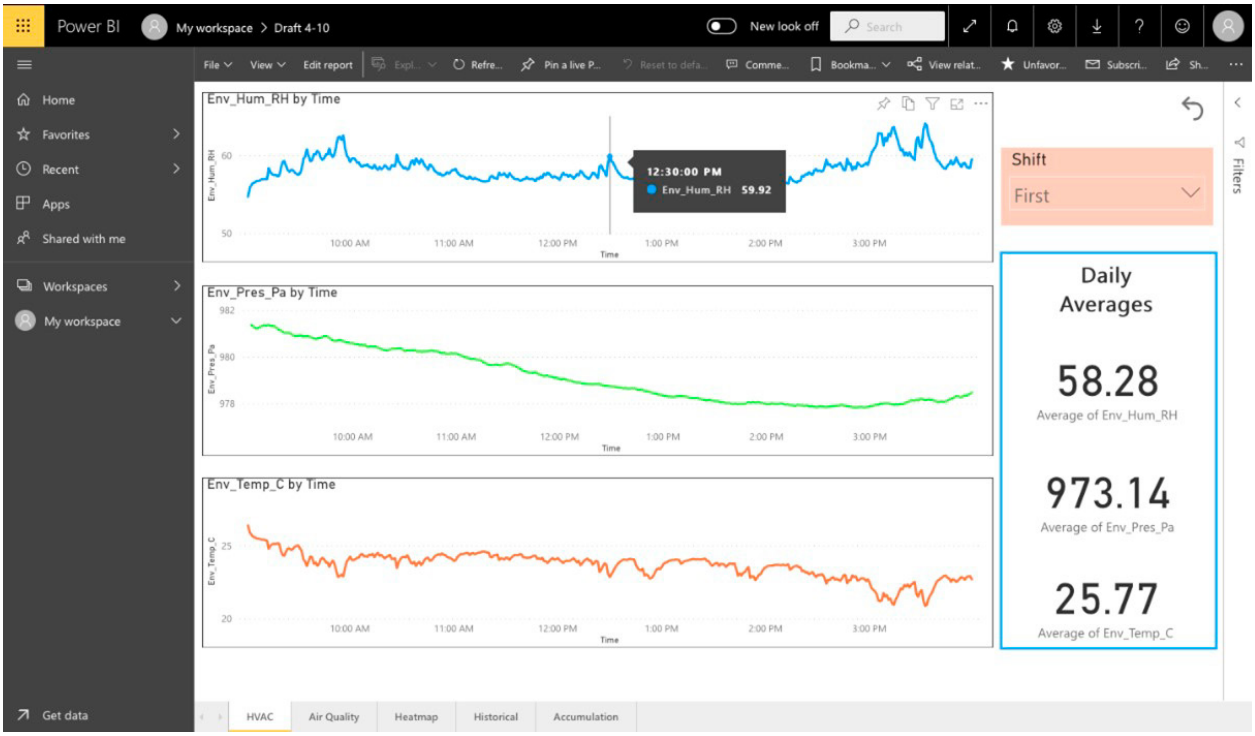
Appendix A. Mioty data transmission outline enlarged from Figure 3



Appendix B. PowerBI based visualization of temperature, pressure, and humidity for one sensor output enlarged from Figure 5



Appendix C. PowerBI based visualization of air quality for one sensor output enlarged from Figure 6