IoT-based real-time wind data prediction for safety monitoring and alerting on construction sites

by

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Prédiction des données de vent en temps réel pour la surveillance et l'alerte de sécurité au chantier, basée sur l'Internet des objets

Siamak RAJABI

RÉSUMÉ

Les appareils portables intelligents sont de plus en plus utilisés en raison de leur potentiel à fournir un environnement de travail plus sûr pour les travailleurs de la construction. Plusieurs études ont été menées afin d'examiner l'application de ces dispositifs pour améliorer la sécurité sur les chantiers de construction en termes d'interactions entre l'homme et le lieu de travail, ainsi que de surveillance et d'évaluation des risques. Parmi les dangers qui affectent la sécurité des travailleurs au chantier, les chutes constituent la principale cause de blessures et de décès. Plus de la moitié des chutes sont causées par des facteurs environnementaux tels que la neige, la glace, le froid extrême et les vents violents. De plus, en raison du changement climatique continu, la fréquence et l'intensité de ces facteurs environnementaux a augmenté ces dernières années. Les vents à grande vitesse sont l'une des conditions météorologiques les plus impactantes sur les chantiers de construction et l'une des principales causes d'incidents et d'accidents.

Traditionnellement, pour surveiller la vitesse des vents forts sur le site de construction, on utilise des services météorologiques en ligne ou, dans certains cas, la station météorologique située sur le site de construction. Cependant, les méthodes traditionnelles de surveillance du vent ne sont pas adéquates et précises. Premièrement parce que la vitesse réelle du vent varie à différents endroits du site de construction en raison de la forme physique du site et ne correspond pas à la vitesse du vent indiquée sur les sites Web. Deuxièmement à cause du manque de suivi en temps réel des données sur le vent.

Dans cette recherche, une nouvelle solution est proposée pour prédire la vitesse et la direction du vent en temps réel basée sur des capteurs IoT montés sur le casque des travailleurs et un algorithme d'apprentissage automatique supervisé. La solution proposée vise la réduction des risques existants liés au vent sur les chantiers de construction. Les principaux composants de cette solution sont un casque de protection équipé de capteurs à thermorésistance et un composant logiciel qui prédit la vitesse et la direction du vent à l'aide d'un algorithme d'apprentissage automatique et génère des alertes. Pour fournir l'ensemble des données nécessaires à la prédiction du vent pendant le développement du prototype, une soufflerie équipée d'un anémomètre, et une plateforme rotative permettant d'obtenir différentes expositions au vent ont été utilisées. Les données recueillies sont utilisées pour construire un modèle de régression pour l'algorithme d'apprentissage automatique supervisé proposé. L'exactitude et la précision de l'algorithme de prédiction sont comparées aux données recueillies par l'anémomètre de référence. Les résultats suggèrent que la vitesse et la direction du vent peuvent être prédites avec une grande précision en temps réel par la solution proposée.

Mots-clés: sécurité de la construction, vitesse du vent, appareils mobiles et portables, équipement de protection individuelle, IoT

IoT-based real-time wind data prediction for safety monitoring and alerting on construction sites

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ABSTRACT

Smart wearable devices are being increasingly used due to their potential to provide a safer working environment for construction workers. Hence, various studies have been conducted to investigate the application of smart wearables to increase the safety of construction sites in terms of human-workplace interactions, as well as monitoring and risk assessment.

Among several hazards affecting workers' safety at work, falling from a height causes the most number of injuries and fatalities. Additionally, more than half of the falls are caused by environmental factors such as snow, ice, extreme cold, and powerful winds. Furthermore, due to continuous climate change, the frequency and intensity of these environmental factors have increased in recent years. High-speed winds are one of the most impactful weather conditions on construction sites and one of the main reasons for incidents and accidents.

Traditionally, to monitor high wind speed at the construction site, specific online weather service sites, or in some cases, the weather station located at the construction site are used. However, the traditional wind monitoring methods are not adequate and accurate. The first reason is the fact that real wind speed varies on different locations of the construction site due to the physical shape of the site and does not correspond to the reported wind speed on the websites. The second reason is the lack of real-time monitoring of wind data.

In this research, a novel solution to predict real-time wind speed and direction based on IoT sensors mounted on workers' hardhats and a supervised machine learning algorithm is proposed. The proposed solution corresponds to reducing the existing wind-related risks at construction sites. The main components of the solution are a hardhat equipped with hot-wire sensors and software component that predicts the wind speed and direction using a machine learning algorithm and provides alerts. To create a dataset for wind prediction, a wind tunnel equipped with an anemometer, a rotational platform to provide various wind exposures are used. The gathered data is used to build a regression models for the proposed supervised machine learning algorithm. The accuracy and precision of the prediction algorithm are compared to the data collected by the reference anemometer. The results suggest that the wind's speed and direction can be predicted with high accuracy in real-time by the proposed solution.

Keywords: construction safety, wind speed, wearables, personal protective equipment, Objets connectés - IoT

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LIST OF ABBREVIATIONS

ETS	École de Technologie Supérieure
ASC	Agence Spatiale Canadienne
PPE	Personal Protective Equipment
IoT	Internet of things
BIM	Building Information Modeling
WSN	Wireless Sensor Network
OSHA	Occupational Safety and Health Administration
SLR	Systematic Literature Review
RFID	Radio Frequency Identification
WiFi	Wireless Fidelity
ML	Machine Learning
DSR	Design Science Research
PTC	Positive Temperature Coefficient
DCS	Data Collection Station
UML	Unified Modeling Language
BLE	Bluetooth Low Energy
SPP	Serial Port Protocol
DC	Direct Current
USB	Universal Serial Bus

GBDT	gradient boosting decision tree
MAE	Mean absolute error
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
RMSD	Root Mean Square Deviation
PETG	Polyethylene terephthalate glycol
CNC	Computerized Numerical Control
TCP	Transmission Control Protocol
UDP	User datagram protocol
PCB	Printed Circuit Board
LTE	Long-Term Evolution
AI	Artificial Intelligence

LIST OF SYMBOLS AND UNITS OF MEASUREMENTS

m/s	meters per second
cm	centimeter
Mbps	megabits per second
mA	MilliAmpere
C	Centigrade
MW	megawatt
Meter	m
Volt	V

INTRODUCTION

Problem Statement

Potential hazards for workers of the construction industry cause high rates of accidents and fatalities, which make it one of the most hazardous industries in the world (Sanni-Anibire, Mahmoud, Hassanain & Salami, 2020). Extensive studies have been conducted to explore the safety of construction in the relation between humans and the work environment, as well as monitoring and risk assessment. Due to the importance of safety in the construction industry, which is classified as a high-risk work environment, an increasing number of studies aimed at developing smart Personal Protective Equipment (PPE) to protect workers and to prevent fatalities and accidents.

In response to various challenges of construction industry, various forefront technologies have been applied to aim to manage data in construction environment (Li *et al.*, 2017). Falling from dangerous heights and runovers of equipment that might result in critical injuries or death are the main identified risks in construction environments (Kanan, Elhassan & Bensalem, 2018). International reports state that workplace accidents lead to about 48,000 annual death, of which 24.2 percent belong to construction sites (Mehata, Shankar, Karthikeyan, Nandhinee & Hedwig, 2019). Researchers have drawn a conclusion from extracted data that 42 percent of fatalities involve falls, which ranked second in the main causes of accidental death all in the world (Mehata *et al.*, 2019). In this regard, the nature of the task being done at the time of the fall incidents was examined, and the results show that roof falls are unquestionably the most common type of accident. Additionally, more than half of the falls are caused by environmental factors (Huang & Hinze, 2003).

Furthermore, snow, ice, extreme cold, powerful winds, hurricanes, typhoons, tornadoes, torrential rain, and flooding have all increased in frequency and severity as a result of ongoing climate change in recent years (Dalton *et al.*). Schuldt, Nicholson, Adams & Delorit (2021) conducts a systematic literature review of 3,207 articles. These articles were published between 1972 and October 2020. They found that high-speed winds were one of the most impactfull weather conditions on construction sites and one of the main reasons for incidents and accidents. Moreover, the management of safety conditions is hard at the time of high-speed winds. Figure 0.1 demonstrate the effects of adverse weather on the performance of workers, materials, equipment, and logistics while the impact of wind is 14.2% according to this study.

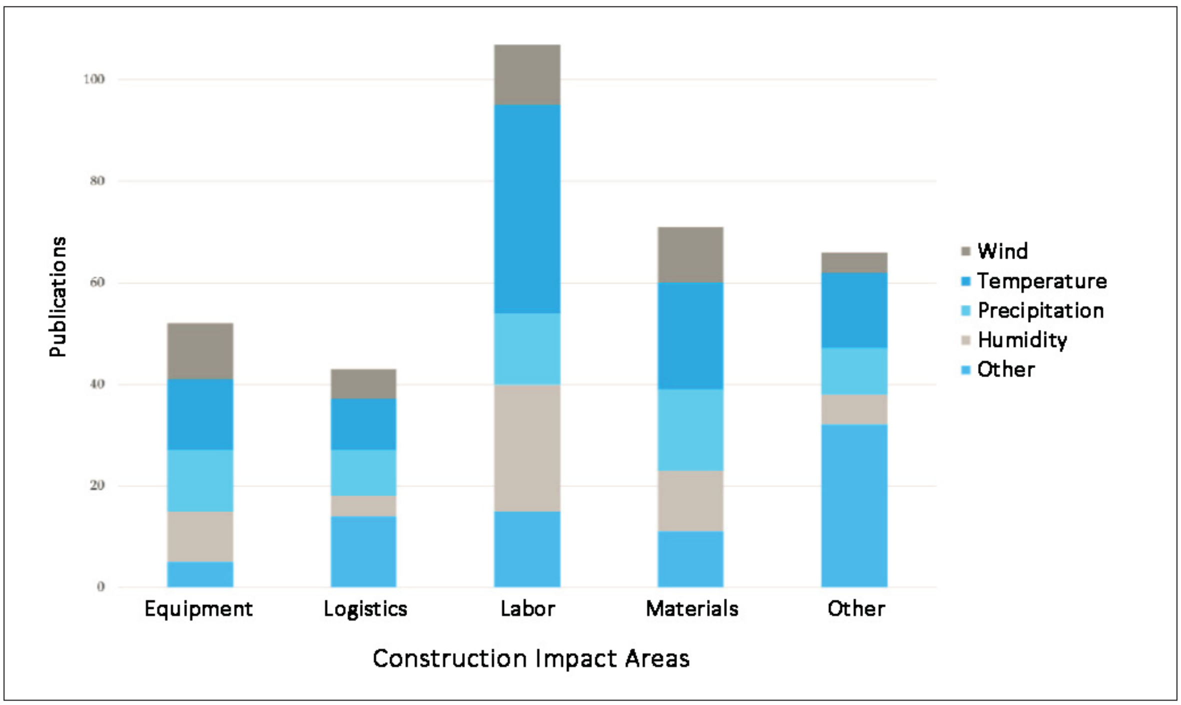

Figure 0.1 Weather factors by construction impact areas
Taken from Schuldt *et al.* (2021)

The Internet of Things (IoT) allows data of many devices and technologies such as sensors, modules to be transferred in real-time for monitoring purposes. By utilizing IoT, data, such as workers' vitals, and workers' positions at the site can be analyzed in real-time. It allows detecting safety hazards, making early decisions, and preventing health problems. IoT transceives data that can provide a supervised safety action based on the workers' health and state in construction sites and real-time feedback.

Research Questions

The main purpose of this research is to improve workers' safety in adverse weather conditions, particularly in high winds. The following research questions were developed to address the above-mentioned safety problems related to wind safety in the construction industry:

1. How to accurately measure the wind parameters (i.e., speed and direction) for each worker and in real-time using IoT technology?
2. How a wind detection system can be integrated in mandatory safety equipment of construction workers?

In this study, in order to answer the questions, a systematic literature review (SLR) is conducted. Regarding the first question, a solution is proposed in which IoT devices and wireless sensor network (WSN) are used to monitor wind speed and direction. To respond to the second question, also a SLR is performed to identify the state-of-the-art in wearable devices and personal protective equipment related to construction safety with the focus on solutions for identifying wind speed and direction. The proposed solution uses a supervised machine learning algorithm that predicts wind parameters using sensors attached to personal protective equipment.

Research Objectives

This research is a part of a larger project which aims to reduce accidents and incidents by providing alerts to workers when exposed to high wind speed. The main objective of this research is to propose and implement a solution to identify the wind speed and direction for each individual worker in real-time using a collection of sensors attached to their personal protective equipment. The research has the following sub-objectives:

1. To propose a method to utilize IoT sensor attached to personal protective equipment for measuring wind speed and direction.
2. To design, implement and test a prototype hardware and software application.
3. To design and implement machine learning models to use the data gathered from sensors for predicting wind speed and direction.
4. To design and implement a data collection station used to create a dataset to be used for training and validation of the machine learning models.

Research Contributions

Numerous publications have investigated various aspects of construction safety. However, there are few research projects in which smart wearable devices are used to improve safety regarding high wind speed on construction sites. Hence, the research contributes to the body of knowledge by introducing a new method and a developed prototype to monitor wind-related data.

Thesis Organization

The current dissertation is structured as follows: Chapter 1 reports on a Systematic Literature Review (SLR) combining bibliometric and qualitative analysis. It examines the state-of-the-art in smart protective equipment and how it can be used for construction automation, and more specifically, for construction safety. Additionally, it investigates the types of sensors and other equipment that can detect wind speed and direction. Chapter 2 elaborated the research methodology and he proposed solution of this research. In Chapter 3 the hardware setup, the data gathering process and the process of training and validation for the Machine Learning (ML) models are explained. In the last part of this Chapter, challenges and limitations of the study are discussed. Finally summary, conclusion and, potential for future work is reported in Conclusion and Recommendations.

CHAPTER 1

LITERATURE REVIEW

To ensure a thorough exploration of the research domain, we conducted a systematic literature review. Safety in construction sites, smart wearables, personal protective equipment (PPE), internet of things (IoT), sensors, wireless sensor network (WSN), and machine learning were the main concepts studied, and they will be defined in Section 1.1. In order to systematically analyze and visualize the trends in smart PPE for construction safety, especially those which can detect wind speed and direction, we conducted a combined scientometric and qualitative analysis. A large dataset of smart PPE applications and wearables in construction were investigated, then using qualitative analysis, those related to construction safety improvement via the implementation of IoT were explored (presented in Section 1.2).

1.1 Definition of The Main Concepts

In each industry, work safety has become a top priority. As a result, workplaces such as surface and underground mining, power plants, factories, and construction sites are exploring new technologies and ideas. One of these new technologies is sensor-equipped wearable devices, such as smartphones and smartwatches. They are becoming more popular as their sensors can be used to monitor environmental hazards, location, movement, heart rate, and more. It is possible to improve the level of safety in any workplace by integrating these wearable devices and Personal Protective Equipment (PPE)) (Adjiski, Despodov, Mirakovski & Serafimovski, 2019). Since each wearable device can have one or more sensors to collect data from its environment, combining these features with the Internet of Things (IoT) could result in another concept known as a wireless sensor network (WSN). Wearable technologies that can communicate with their environment and provide wireless monitoring using IoT have the potential to increase work performance and minimize error (Rooney, Bauer & Scotton, 2006)).

1. **Construction Safety:** In the last four decades, the construction industry's safety has vastly improved. Between 1973 and 2004, the number of fatalities dropped from 71 to 11.6 per 100,000 people, while the rate of injuries dropped from 8,520 to 4,478 per 100,000 people (Figure 1.1) (Navon & Kolton, 2006). Increasing the usage of new methods to prevent injuries has contributed to this improvement (Esmaeili & Hallowell, 2012). The ability to complete construction tasks, also known as task feasibility, is directly affected by weather events. In fact, adverse weather conditions have the biggest influence on the timeline of construction sites. These events can have a negative impact on worker safety, potentially resulting in legal consequences (Schuldt *et al.*, 2021), and adverse weather is one of the main issues related to the safety of construction sites.

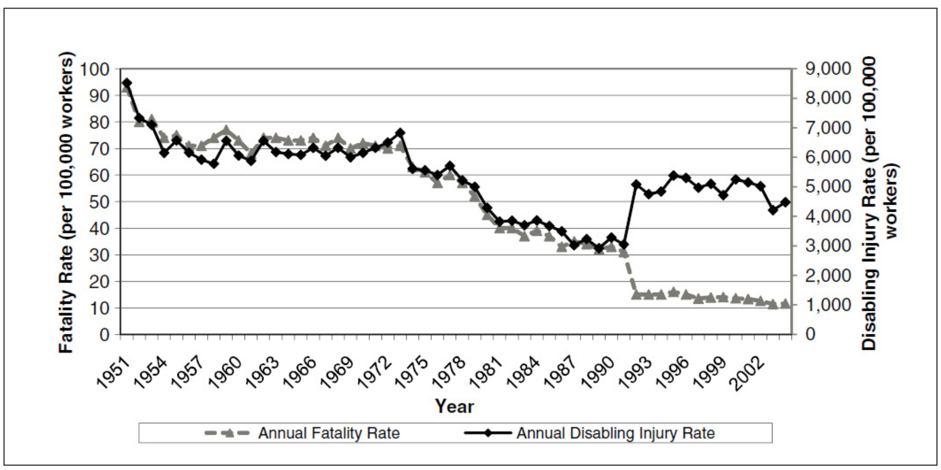

Figure 1.1 Construction fatality and disability rates between 1952 and 2004
Taken from Esmaeili & Hallowell (2012)

2. **Construction Site Wind Safety Regulations:** Regarding wind-related safety issues, some tasks should be considered by default. For example, we should check the temporary structures to see if they are secure and safe. On the other hand, some conditions should be checked in real-time. For instance, winds in excess of 6 m/s can blow dust, debris, and other foreign particles into the eyes. Another example, when the winds in excess of 8 m/s can

affect the balance. Therefore, workers should never work on scaffolding, roofs, or other elevations when the wind is >8m/s.[1]

According to the Occupational Safety and Health Administration (OSHA), 'high wind' normally means winds exceeding 17.8 m/s ("such velocity that could blow an employee from an elevated location"), or 13.3 m/s if the work involves material handling ("could cause an employee or equipment handling material to lose control of the material").[2]

3. **Smart wearables, and Personal Protective Equipment (PPE):** Information about workers and their environment can be extracted using Smart Personal Protective Equipment (PPE) and wearable technologies and its use can result in a significant reduction in the rate of accidents and occupational illness. Various sectors, such as construction, mining, and electricity, have begun to invest in improving worker safety by implementing new technologies or "smart technologies" in the workplace. These technologies can be used to supervise and protect people within a work environment, establishing a PPE ecosystem that protects employees' health and safety (Márquez-Sánchez, Campero-Jurado, Herrera-Santos, Rodríguez & Corchado, 2021).

   Such equipment must be adjusted to the needs of the employees, providing protection without inhibiting their ability to perform their tasks normally. There are several types of smart PPE technologies that can be used to monitor various types of industrial environment data (Márquez-Sánchez *et al.*, 2021). In this literature review, we will search for personal protective equipment, wearable devices, or sensors that can detect wind speed and direction for the construction sites and other industries.

4. **Internet of Things (IoT), Sensors:** The Internet of Things (IoT) is a new technological paradigm that envisions a worldwide network of interconnected equipment, devices, and gadgets. Also known as the Internet of Everything or the Industrial Internet, the Internet

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[1] https://wilkinssafety.co.uk/2018/01/ working-safely-high-winds

[2] https://www.osha.gov/laws-regs/regulations/standardnumber/1926/1926.968

of Things is widely recognized as one of the most crucial areas of future technology. It is sparking significant interest from a variety of industries (Lee & Lee, 2015), and in the future, many of the items surrounding us will be connected in some way under the IoT (Gubbi, Buyya, Marusic & Palaniswami, 2013).

When devices can interact without any limitation in location and combine with vendor-managed inventory systems, user support systems, business intelligence tools, and business analytics, the true value of the IoT may be completely realized. Radio Frequency Identification (RFID), Wireless Sensor Networks (WSN), middleware, cloud computing, and IoT application software are five techniques that are frequently adopted for the implementation of successful IoT-based products and services (Lee & Lee, 2015).

The trend towards global information and communication networks is already observable, with the increasing availability of WiFi and 4G-LTE wireless Internet access. The arrival of the Internet has resulted in extraordinary levels of communication amongst humans.The integration of objects to create a smart environment will be the next revolution (Gubbi *et al.*, 2013). "SENSOR is an entity capable of sensing the state of some underlying systems and transmitting information about that state to some higher-level entity" (Hellerstein, Hong & Madden, 2003; Rooney *et al.*, 2006). Sensors are vital components of smart and wearable technologies incorporated in PPE. In addition, they are one of the most crucial elements of the IoT (Makris, Skoutas & Skianis, 2012; Adjiski *et al.*, 2019).

5. **Wireless sensor network (WSN):** A WSN is a set of sensor nodes that work together to sense and manage an environment. These nodes are small, low-power devices, connected via wireless links and able to communicate with each other. The main elements of a typical WSN architecture are (1) sensor nodes, (2) gateway, and (3) observer (Figure 1.2) (Kocakulak & Butun, 2017).

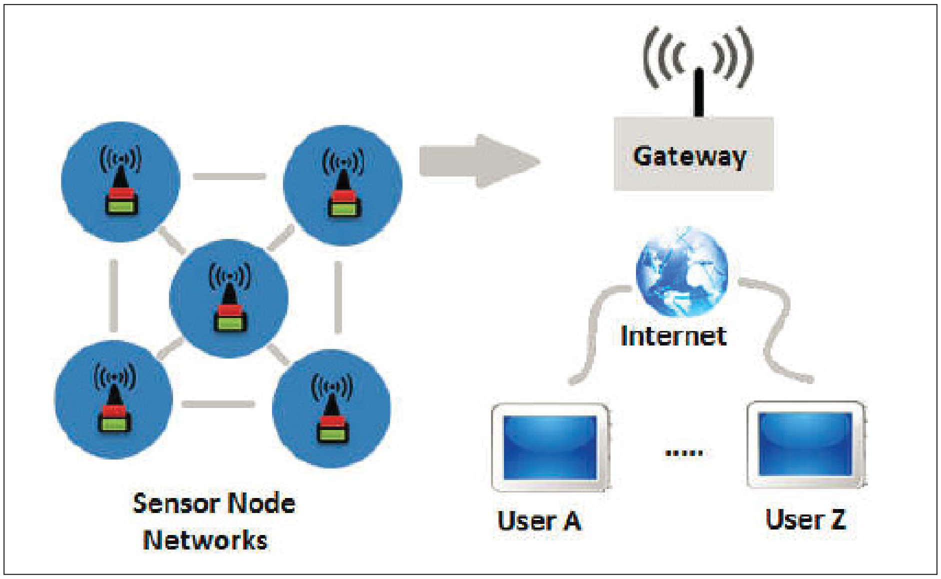

Figure 1.2 The architecture of a typical WSN
Taken from Kocakulak & Butun (2017)

6. **Machine Learning (ML):** Machine Learning (ML) is an effective method to extract information from large volumes of data. Machine-learning applications span from machine perception and text interpretation to health care, genomics, and self-driving automobiles. Much machine learning literature has focused on improving the accuracy and efficiency of training and inference algorithms (Polyzotis, Zinkevich, Roy, Breck & Whang, 2019). It is important to monitor the quality of the data used for machine learning because data errors can have a negative impact on the quality of the created model. On the other hand, data validation is neither a new challenge nor is it unique to machine learning, so we can use ideas from other domains (Figure 1.3) (Polyzotis *et al.*, 2019). One way to validate a machine learning model is cross-validation. In the machine learning field, cross-validation is the de facto standard for model validation (Keevers, 2019). There are several cross-validation methods, including Leave One Out, Stratified Cross-Validation, and K-Folds. For most applications, k-fold cross-validation is the conventional ML validation approach (Schnaubelt, 2019).

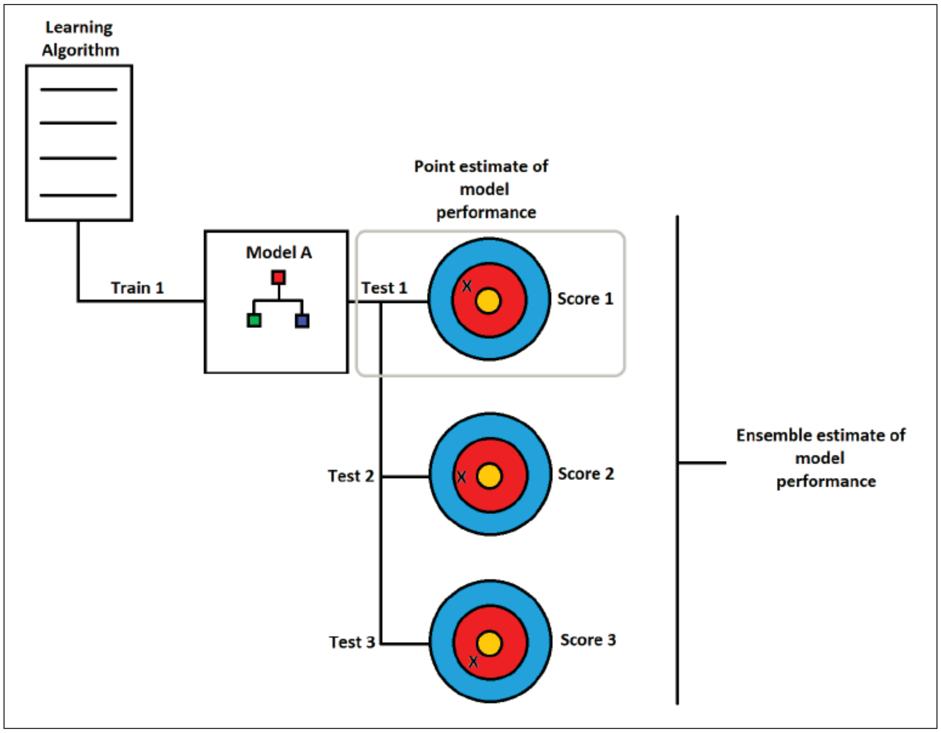

Figure 1.3 Estimating the performance of a specific model
Taken from Keevers (2019)

1.2 Methodology of The Literature Review

This study conducts a Systematic Literature Review (SLR) consisting of the following steps: identification, evaluation, and interpretation of a field of research and that can be reproduced with the same protocol by other researchers (Kitchenham, 2004). A combination of science mapping and qualitative analysis was utilized to provide a comprehensive overview of the status in the field. Science mapping aims to visualize the structural and dynamic aspects of a research domain. The steps of science mapping are data retrieval, preprocessing, network extraction, normalization, mapping, analysis, and visualization, and it helps the researcher draw conclusions based on collected results. Different approaches, including Co-word analysis, co-citation analysis, and journal bibliographic coupling, are used in science mapping (Cobo, López-Herrera, Herrera-Viedma & Herrera, 2011). Science mapping can indicate the potentials of a specific field. One of the objectives of the current literature review is to study the potential of a real-time wind speed and direction detection system for construction site safety.

1.2.1 Bibliometric Analysis

This study aims to present a holistic overview of wind measurement methods and smart PPE applications in construction safety to meet the goal and explore the concepts in depth.

1.2.2 Keywords

The following keywords present the query used to retrieve the most relevant publications in online databases, and Figure 1.4 provides a visual illustration of the query:

- **Importance of wind measurement in construction sites:** (construction*) AND (Wind* OR airflow) AND (IoT OR internet of things OR sensor* OR WNS OR wireless network*) AND (Safety).
- **Integration of IoT and PPE for safety:** (IoT OR internet of things OR sensor* OR WNS OR wireless network*) AND (safety) AND (hardhat OR hardhat OR PPE OR personal protective equipment OR wearable*).
- **Integration of PPE and wind sensors:** (wind OR airflow) AND (IoT OR internet of things OR sensor* OR WNS OR wireless network*) AND (hardhat OR hardhat OR PPE OR personal protective equipment OR wearable*).
- **Closest to our work:** (construction*) AND (Wind* OR airflow) AND (IoT OR internet of things OR sensor* OR WNS OR wireless network*) AND (Safety) AND (hardhat OR hardhat PPE OR personal protective equipment OR wearable*).

Items	Eng. village	IEEE	Web of Science	Scopus	Dimensions	PubMed
Importance of wind measurement in construction sites	269	25	82	1819	37	6
Integration of IoT and PPE for safety	2732	693	1369	327	483	464
Integration of PPE and wind sensors	310	19	287	55	101	51
Closest to our work	12	1	6	8	1	0

Figure 1.4 Search results (each keyword)

1.2.3 Identification

Once the keywords were identified, online databases were queried to retrieve the most relevant papers. The targeted databases were Engineering Village, IEEE, Web of Science, Scopus, Dimensions, and PubMed. Some 9,157 records were identified and are illustrated in Figure 1.5.

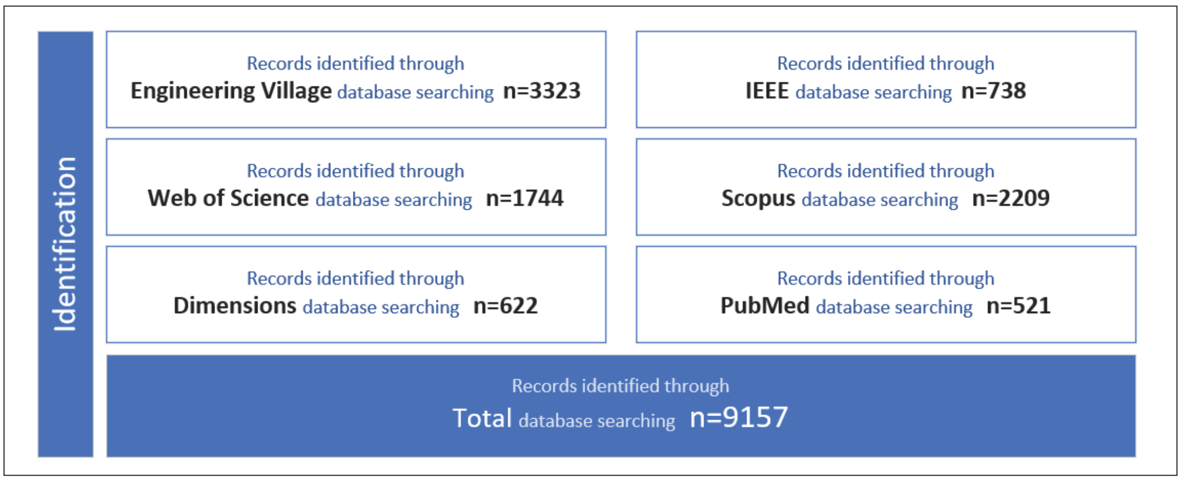

Figure 1.5 Identification steps

1.2.4 Screening and Eligibility

Screening and eligibility include two main steps: duplicate identification and inclusion. The former identifies and subsequently removes the duplicate articles from the database, while the latter only brings the most pertinent point of the study into consideration. As mentioned, the search related to this query returned 9,157 results on which a preliminary screening was performed based on duplicate papers, bibliographic database analysis, and title and abstract. Based on the duplication criterion, 5,315 papers were removed. Based on bibliographic database analysis, which included co-occurrence, co-authorship, and coupling, 3,001 papers were excluded. Some 654 papers were eliminated after screening based on title and abstract. Finally, after the full-text analysis to select the most appropriate papers, 116 papers were excluded (Figure 1.6).

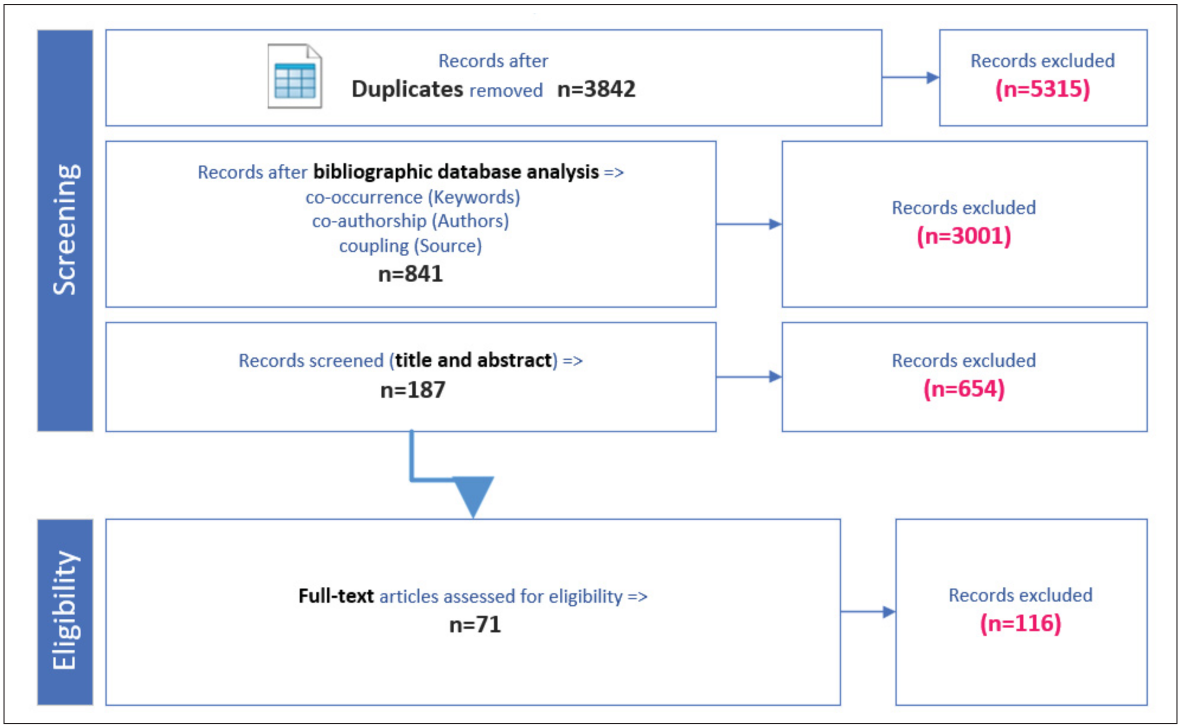

Figure 1.6 Screening and eligibility steps diagram

Furthermore, forward and backward snowballing added 5 more papers to the selected sample. After the entire screening process, which is illustrated in Figure 1.7, some 76 papers were retained as the final sample for the systematic review synthesis.

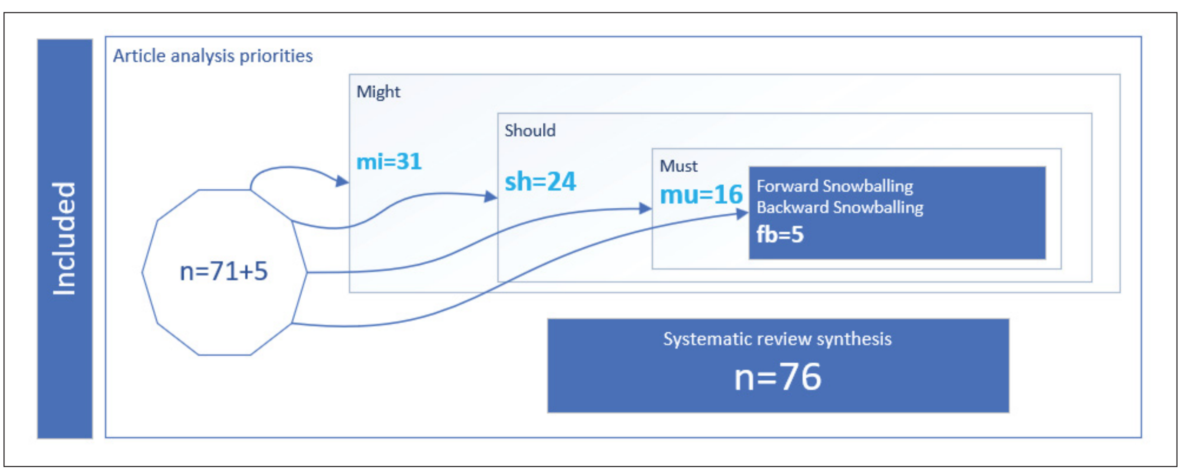

Figure 1.7 Systematic review synthesis

1.3 Findings

1.3.1 Keywords Co-occurrence Analysis

A publication's main focus of research, fundamental content, the scope of study, and bounds of a specific domain are indicated by keywords (Su & Lee, 2010). A visual representation of the keywords illustrates the relationships between the studied field's various subdomains. Due to the significance of these relationships, a keywords co-occurrence analysis was done. VOSviewer visualizes bibliometric networks using a distance-based approach (Van Eck & Waltman, 2014). Further data analysis of the files exported from VOSviewer was conducted using Gephi, which merges similar areas of study (i.e., IoT, WSN, safety management, and RFID). Various representations of the results are depicted in the following figures. Figure 1.8 illustrates the keyword network results by VOSviewer, which includes 25 nodes. Two more representations of the results in terms of density and publication date are illustrated in Figure 1.9 and Figure 1.10. Apart from the Construction site and Safety, which are the focal fields of study of this literature review, "wearable sensors", "wind", "wireless sensor network" and "machine learning" attract the attention of researchers. Figure 1.11 illustrates the network of topics relating to wearable sensors keywords.

1.3.2 Direct Citation

As discussed before, a bibliometric network consists of nodes and edges. The nodes can represent publications, journals, researchers, or keywords, whereas the edges indicate relations between pairs of nodes. Citation relations, keyword co-occurrence relations, and co-authorship relations are the most commonly studied types of relations (Van Eck & Waltman, 2014). While discussing citation relations, it might be distinct by direct citation relations, co-citation relations, and bibliographic coupling relations. Direct citations offer a more direct indication of the relatedness of publications in comparison with co-citation and bibliographic coupling. Figure 1.12 illustrates the citation and Figure 1.13 illustrates the density of authors in the field of study.

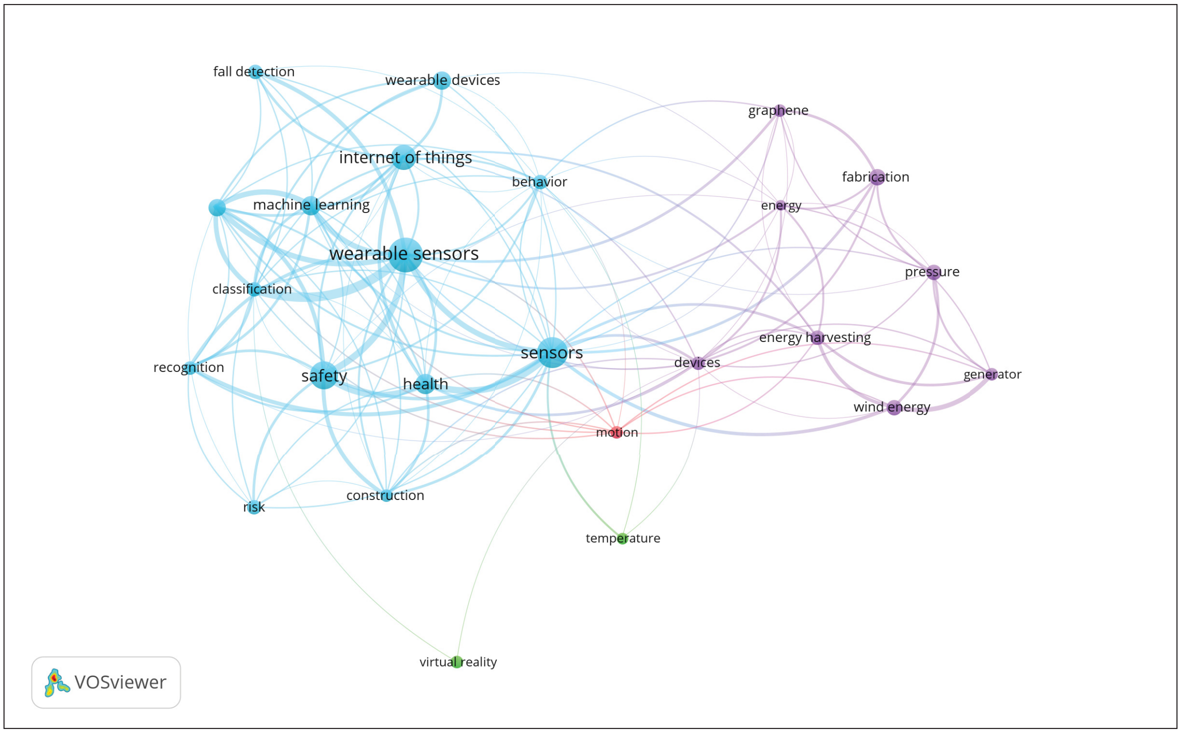

Figure 1.8 Keyword network graph

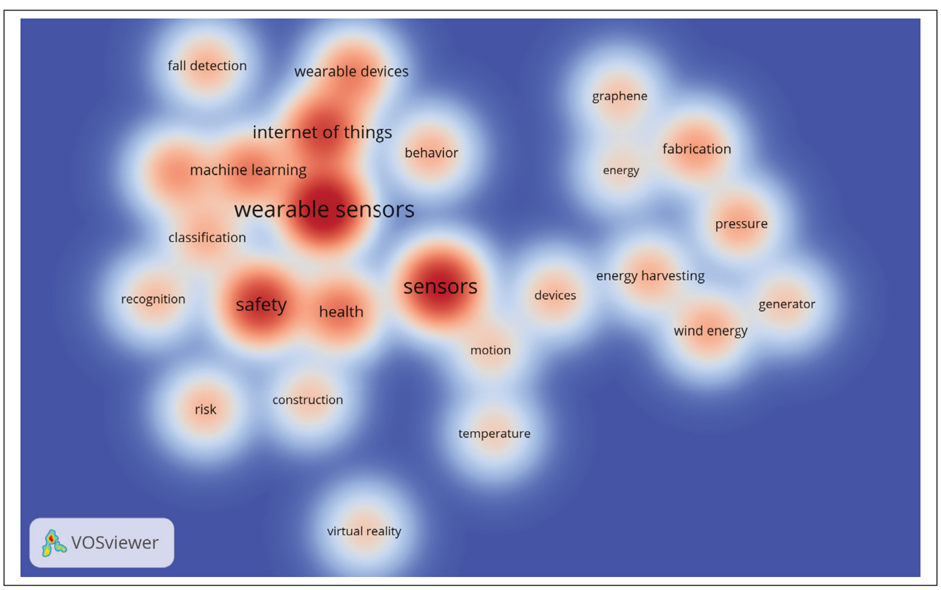

Figure 1.9 Keyword network graph (density)

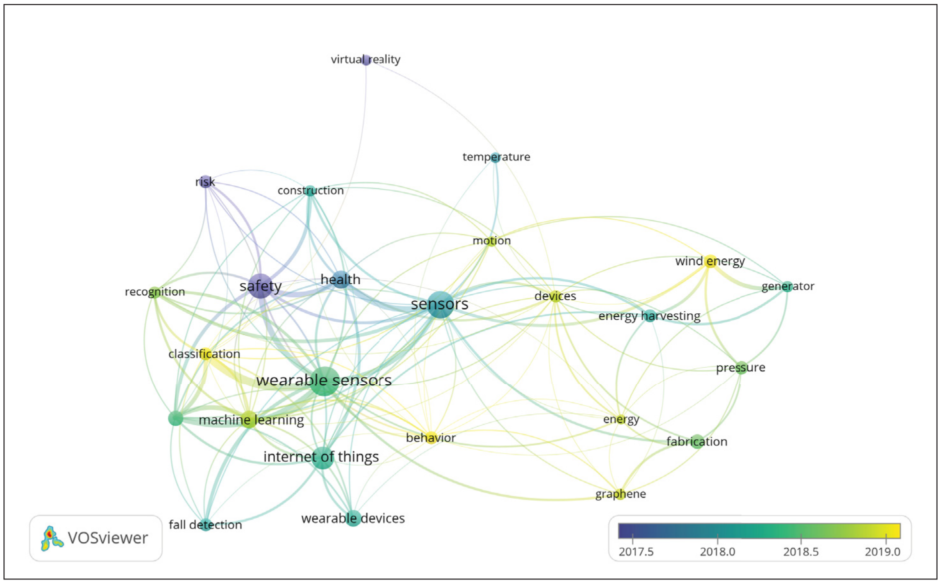

Figure 1.10 Keywords network graph (date)

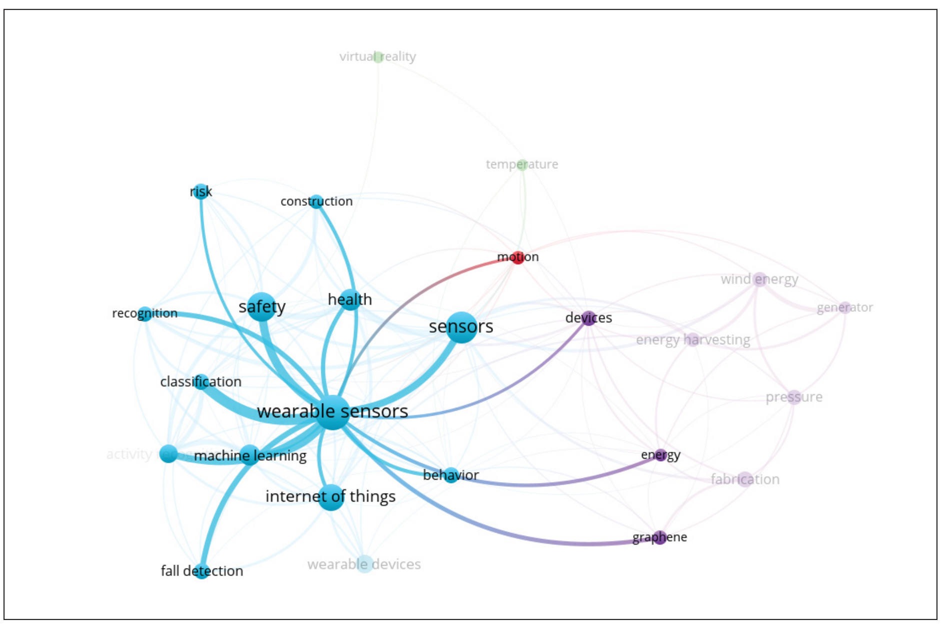

Figure 1.11 Wearable sensors keywords network

As discussed, a bibliometric network consists of nodes and edges. The nodes can represent publications, journals, researchers, or keywords, whereas the edges indicate relations between pairs of nodes. Citation relations, keyword co-occurrence relations, and co-authorship relations are the most studied types of relations (Van Eck & Waltman, 2014). As for citation relations, they can be distinguished according to direct citation, co-citation, and bibliographic coupling. Direct citations offer a more direct indication of the relatedness of publications in comparison with co-citation and bibliographic coupling. Figure 1.12 illustrates the citation relations and Figure 1.13 illustrates the density of authors in the field of study.

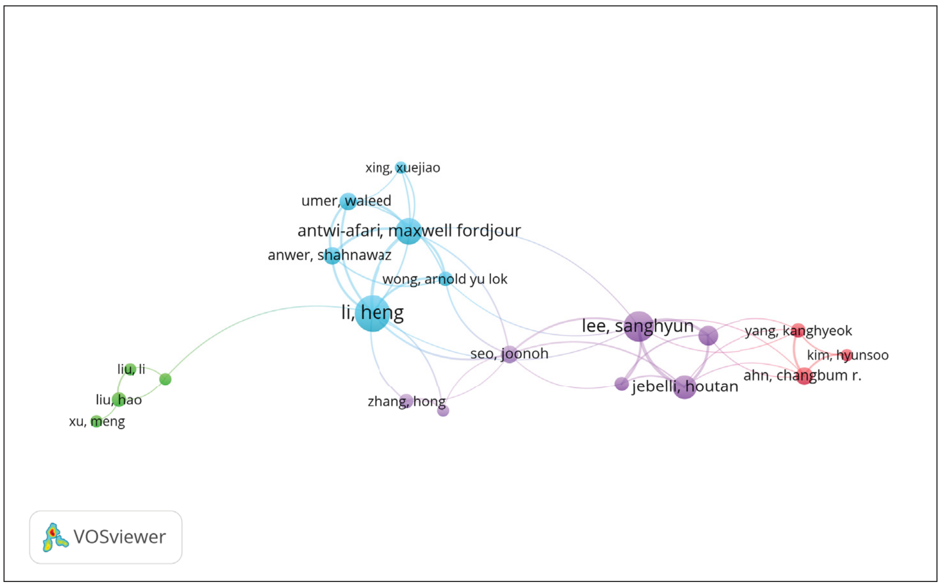

Figure 1.12 Citation of authors

1.3.3 Bibliographic Coupling

The overlap in the reference lists of publications is presented by bibliographic coupling. The larger the number of references two publications have in common, the stronger the bibliographic coupling relation between the publications. Although bibliographic coupling was introduced earlier than co-citation, it initially received less attention in the literature on visualizing bibliometric networks. However, in more recent years, the popularity of bibliographic coupling increased considerably (Van Eck & Waltman, 2014). Figure 1.14 illustrates bibliographic coupling in terms of source with their timeline, which presents the date of publication. As illustrated, the most common journal in the field of study is “Sensors”.

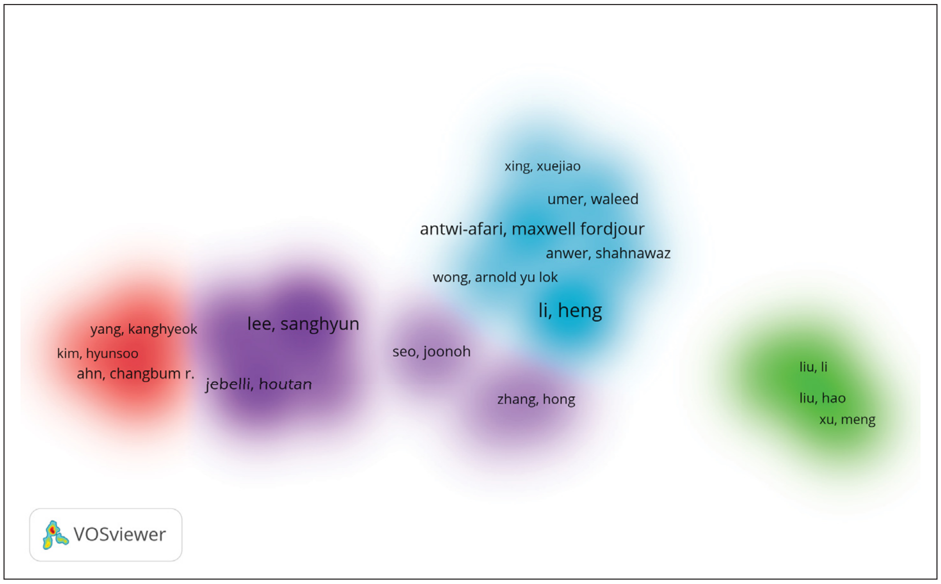

Figure 1.13 Citation of authors (density)

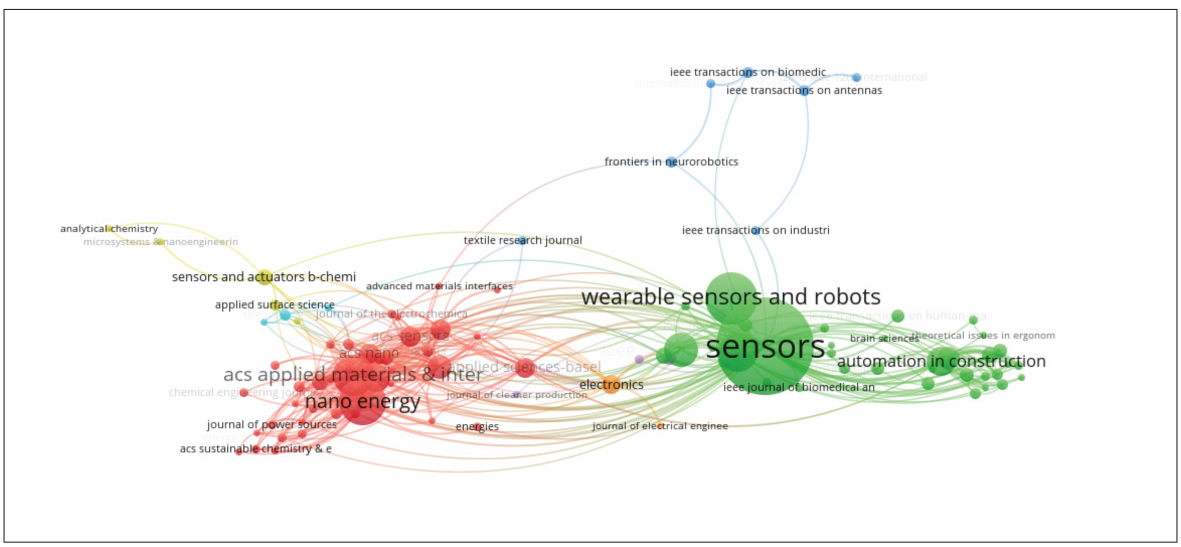

Figure 1.14 Bibliographic Coupling

1.3.4 Qualitative Analysis

In Section 1.2.1 the integration of construction safety, wind detection, and PPE was investigated using a biblio-metric analysis. Then, the most relevant publications were chosen using a systematic literature review, to better examine the achievements pertaining to this topic.

These articles are categorized into three parts to clearly distinguish the various subdomains: (Construction Safety and Wind), (Construction Safety and PPE), and (PPE and Wind).

1.3.4.1 Construction Safety and Wind

This part of the literature looks at the importance of construction safety, worker safety, and the effects of wind. In fact, we reviewed articles to see how weather conditions, specifically wind characteristics, delay construction projects. We assumed that by covering this topic, we might find the importance of wind detection for both construction projects and labor in this industry. Weather conditions affect the progress of construction projects around the world. The three most important weather elements that slow down construction progress are extreme temperature, high wind, and precipitation. Any effort to increase the speed of construction and reduce the rate of accidents and incidents by improving planning, organizing work, and decreasing the negative impact of weather on construction projects needs to consider these climate conditions (Schuldt *et al.*, 2021).

Temperature, wind, humidity, and precipitation are the most researched weather parameterss (Budhathoki & Zander, 2019; Ghani, Tariq, Javed, Nisar & Tahir, 2020; Acharya, Boggess & Zhang, 2018; Moohialdin, Lamari, Miska & Trigunarsyah, 2019). These meteorological elements have different effects on labor, materials, and machinery. Temperature variations often affect the length of time that laborers can work outdoors, as well as limit the equipment that can be used if situations become dangerous. Winds could have an impact on materials and workers. Unconstructed materials and debris could be blown around and endanger people. In addition, strong winds can put machinery performance at risk (Schuldt *et al.*, 2021).

The risk to labor safety is the principal cause of increased productivity delays. Labor accidents are more likely serious when wind speeds are high (Larsson & Rudberg, 2019). For example, due to the high risk of falls, workers are forbidden from doing construction jobs on scaffolding during strong winds. Furthermore, painting in high winds might cause paint to fall on laborers below (Ballesteros-Pérez, Smith, Lloyd-Papworth & Cooke, 2018). As mentioned, high wind speeds also affect equipment. For example, based on a study between 2000 and 2010, more than 1,100 accidents involved cranes that led to nearly 800 fatalities[3].

Larsson & Rudberg (2019) described the impacts of wind on carrying capabilities and discovered that wind speeds higher than 14 m/s could cause machinery work stops in construction sites. In another study, Shahin, AbouRizk, Mohamed & Fernando (2014) found that crane activity should stop if wind speeds exceed 50 km/h.

By looking at the relationship between wind speed and related construction occurrences and fatalities, the level of destruction and effects of buildings when exposed to high wind speeds was studied by Gholitabar & Griffis (2019). To detect possible patterns in wind-related claims and building incidents, as well as to identify geospatial risk, data were analyzed. The authors gathered data in two different aspects: (1) all construction-reported accidents and incidents, (2) data from weather stations over five years, and from their analysis, they proposed a method to detect the level of risk during high-speed winds (Gholitabar & Griffis, 2019).

The data they collected was categorized into three parts: Percentage of reports per category relating to windy conditions, the number of complaints per day on regular days and windy days, and geographical mapping of the city's complaints and a relationship between local wind levels and the number of reports for each urban neighborhood. From their analysis, they found that the most common complaints involved items that were dropping or at risk of dropping. Damaged or cracked surfaces, as well as signs of risk of toppling, were the other most common categories of issues, which were likewise related to wind speed (Gholitabar & Griffis, 2019).

Furthermore, the statistics showed that the number of reports each day during windy conditions was higher than on normal days. The frequency of construction incidents or accidents also appears to be influenced by wind speed (the greater the wind speed, the higher the number of incidents or accidents). As shown in Figure 1.15, they divided the reports of accidents and incidents for windy and non-windy days into four categories: wind speeds less than 20 mph (considered as normal, non-windy day); wind speeds of 20 - 25 mph (considered as windy);

[3] https://www.windcrane.com/blog/construction/ tower-cranes-wind-speed-lifting-guidance

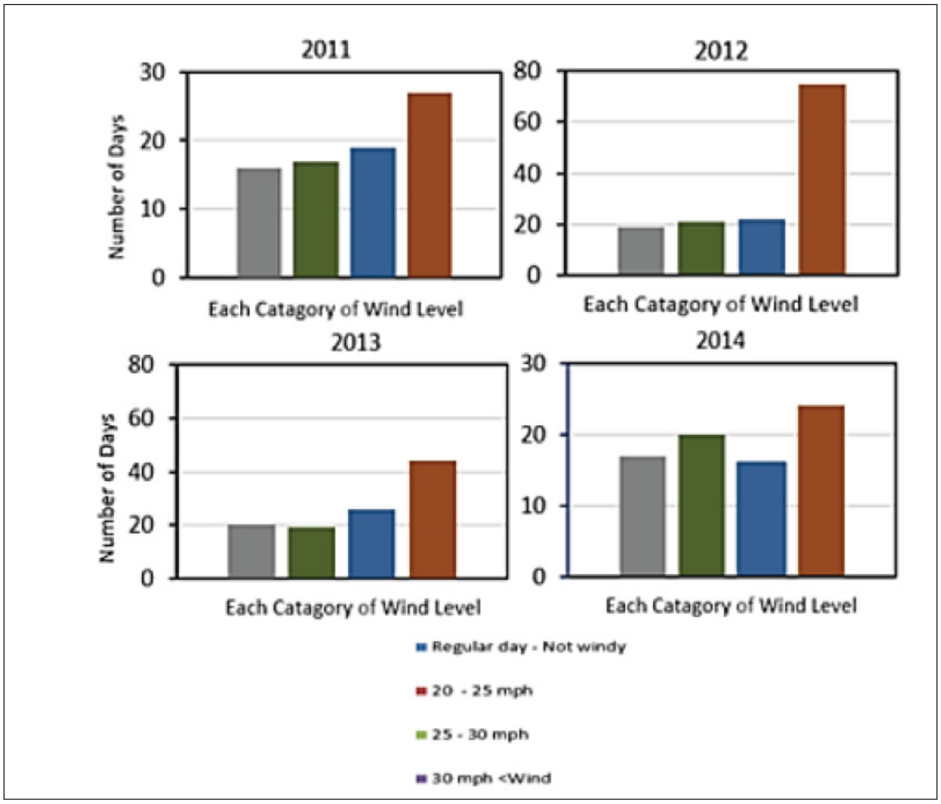

Figure 1.15 For each type of wind speed, the regularity or number of reports of accidents or incidents per day
Taken from Gholitabar & Griffis (2019)

wind speeds of 25 - 30 mph and wind speeds higher than 30 mph. Based on their findings, the percentage of accidents and incidents on days with a wind speed higher than 25 mph is greater than on normal days or days with a wind speed less than 25 mph (Gholitabar & Griffis, 2019).

In another report (Dalton *et al.*), various damages to the construction sites were linked to weather conditions. Different types of weather conditions and their effects on sites were explained, but we focused solely on the wind. Strong winds can affect the sites in different ways, such as wind entering a structure's shell, roof lifting, flying material, etc. At the same time, different projects and sites might be affected by strong winds, for example, buildings, factories, warehouses, hydraulic structures, bridges, etc. It is important to note that based on their findings, damage caused by strong winds could depend on other wind characteristics, such as the duration of the wind change and the wind's direction. Nevertheless, there are steps that could be taken to decrease and prevent damage caused by strong winds.

Similarly, strong winds can affect the safety of workers. While there were fewer studies on the effects of wind on workers, it can be argued that wind could cause various types of injuries, by pulling items from the worker's hands or projecting construction material through the air onto workers, such as large flying barriers or small items that could cause eye injuries .[4]

In either case, when it comes to the sites or workers, many incidents and accidents could be prevented by taking appropriate and prompt action. For example, work duties that become risky in windy situations should be suspended or eliminated entirely, worksite layout should be planned according to the direction of the wind, such as placing vehicles and equipment opposite from where the worker exits, wearing safety equipment such as glasses, be completely aware of site conditions or special items that are more important and protect them from the effects of strong winds, and securing all unstable sheet surfaces and other loose objects (Dalton *et al.*).

1.3.4.2 Construction Safety and PPE

In this Section, we reviewed personal protective equipment (PPE), in particular hardhats. Based on the literature, studies on the improvement of safety through the addition of sensors to a smart hardhat could be categorized into four topics: self-localization, human biometrics, proper-wearing management, and gas detection.

Abderrahim, Garcia, Diez & Balaguer (2005) designed a system to record and analyze the data of workers and equipment locations. It could prevent workers from entering dangerous zones and prevent hazardous accidents (Figure1.16). The data from both the PPE and workers (data from a GPS affixed to the hardhat) were transmitted by RF to a center. It was also possible to use a camera attached to the hardhat to capture the environment when the worker was in a dangerous zone. If the worker was in danger, it could be announced by voice communication.

[4] https://www.safetytalkideas.com/safetytalks/high-wind-dangers-construction/

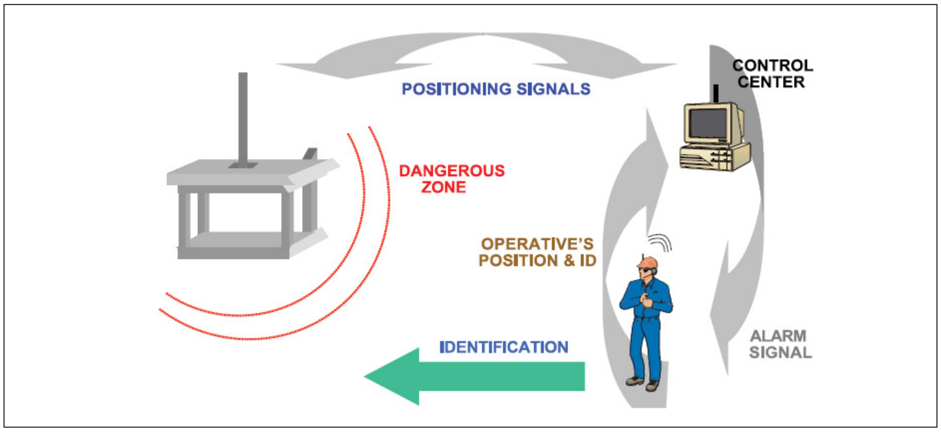

Figure 1.16 Flow of information and protection design parts
Taken from Abderrahim *et al.* (2005)

Fyffe, Langenderfer & Johns (2016) designed a prototype to transmit vital data by mobile to the administration. Information such as worker's body temperature, heart pulse, worker ID, time, and impact force was sent via a "Global System for Mobile Communication (GSM)". Workers could be notified by a LED alarm if their biometric data exceeded a set threshold.

To provide a safer work environment, Alvarez, Casinillo, Goich & Soares (2017) implemented a system to notify workers by illuminating a series of LEDs on the hardhat. This enabled communication between workers and the administration, monitoring of the worker's location, and speech recognition to record notes. Also, the system could take a photo of the site and shine a light to improve the workers' vision. In addition, they used WiFi and a mobile application to provide access to documents, contact lists, etc.

To improve workers' safety in an industrial site, Kim, Wang, Min & Lee (2018) attached a three-axis accelerometer sensor to a hardhat. As a result, they could detect if the hardhat was worn correctly, incorrectly, or was not worn with an accuracy of 97%. Figure 1.17 illustrates this: the sensor data is sent to the smartphone via a Bluetooth low-energy module, the smartphone sends this data to the database, and if a worker is not wearing a hardhat or is wearing it incorrectly, an alarm message is sent to the head of safety, for example.

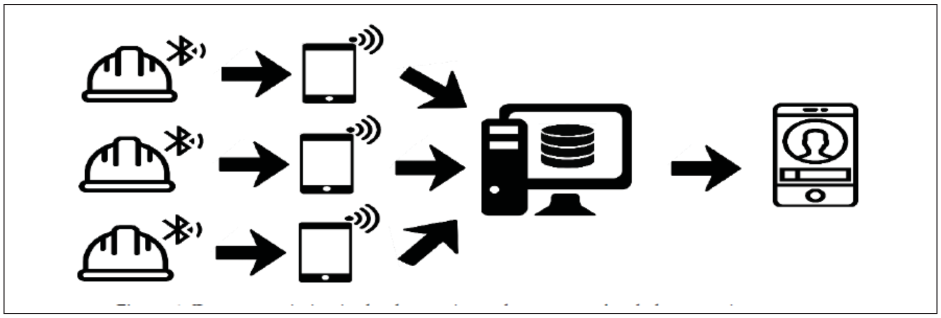

Figure 1.17 The three-axis accelerometer safety hardhat sensor system transmits data
Taken from Kim *et al.* (2018)

Mehata *et al.* (2019) developed smart wearable devices to monitor the health and safety of workers. The main functionalities of the developed systems were fall detection of workers, lifesaving notifications, and monitoring workers' vitals such as heart rate and temperature with sensitivity to abnormalities. Decreasing the number of deaths in construction sites by providing a safer worksite was the primary goal of this system. The system included wearable devices such as a smart band and hardhat equipped with sensors and electronic components and a cellphone that connected the two components via GSM. While the workers wore the device, they could be monitored in real-time, and any abnormal signals were sent to their supervisor, who could then take prompt appropriate actions if necessary.

The system's three evaluation criteria were comfortability, portability, and reliability. As a health monitoring module, it observed the physical markers of workers such as heart pulse and body temperature. These data were stored continuously in a cloud database. The heartbeat components consisted of a sensor with a pair of LED and LDR, a microcontroller to measure the workers' heart pulse, and a temperature sensor. The safety monitoring module could detect if workers fell or slipped via the accelerometer sensors in the smart hardhat. The accelerometer sensors investigated the acceleration, threshold value and, tri-axial position of the object and helped identify possible incidents.

As illustrated in Figure 1.18, the system was developed in five stages. First, sensors were embedded and activated in the devices; then, components were connected through a sim card.

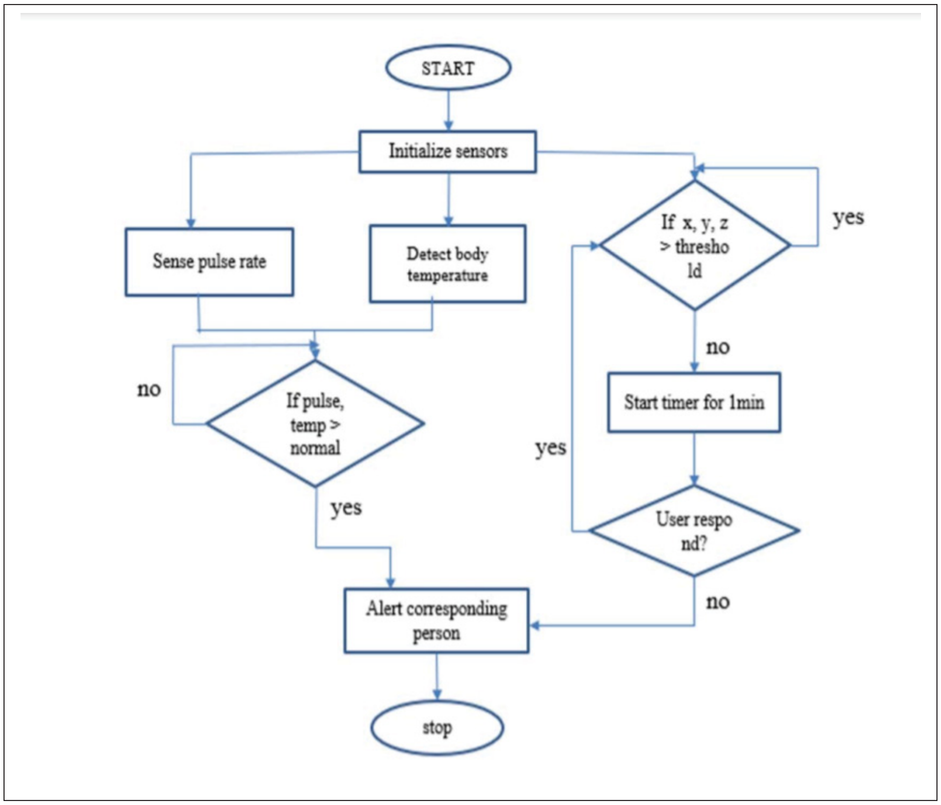

Figure 1.18   Proposed working algorithm
Taken from Mehata *et al.* (2019)

The readings of workers were monitored, and if any abnormality or alert was raised, supervisors were notified. The fall detection algorithm explored and predicted a possible fall based on the accelerometer sensor measurements in comparison with normal values. In a fall detection case, a sudden change to the accelerometer is triggered by exceeding a certain value, which prompts a fall detection notification to the supervisor.

Wu, Rüdiger, Redouté & Yuce (2018) presented a wearable sensor node named WE-Safe, based on LoRa, which is a low-power wide-area network (LPWAN) technology. The sensors monitored levels of carbon monoxide, carbon dioxide, ultra-violet rays, and other general environmental parameters. Data was sent to the cloud using a low-power sensor node connected to a gateway.

The wearable node was programmed to monitor environmental data continuously, that is, every minute, to detect any abnormal or harmful levels of these gases.

Arcayena Jr, Ballarta, Claros & Pangantihon Jr (2019) implemented a prototype hardhat equipped with sensors to monitor workers' biometrics and detect their location (Figure 1.19). The biometric sensor, GPS, accelerometer, and emergency button were connected to a microcontroller. The prototype also included software to collect and analyze data to facilitate further safety actions. Regarding the results, the accuracy of vital signs detection was more than 95%. Also, positioning and identification detection were 100%.

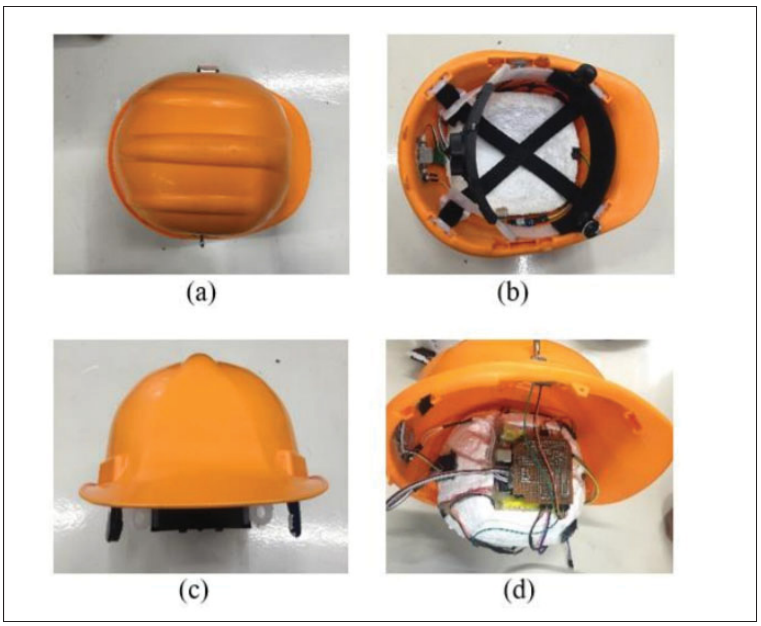

Figure 1.19 (a) Top view, (b) Bottom view,
(c) Front view, (d) Inside view
Taken from Arcayena Jr *et al.* (2019)

Huang *et al.* (2019) implemented a hardhat prototype that included a GPS to detect location, sensors to detect gas leakage, a camera for real-time video and audio connection, a temperature sensor to monitor environment, and a speech recognition application to ease communication.

Altamura, Inchingolo, Mevoli & Boccadoro (2019) proposed a platform named SAFE (Figure 1.21), that integrated a smart object to create a secure shelter that seamlessly monitored worker biometrics in relation to environmental conditions such as dangerous gas and flame and leveraging the potential of IoT using wireless communication technologies. Figure 1.20 illustrates the platform's distributed and crowd-sourced design. It could notify both workers and administration using signaling devices to ensure proper actions in critical situations.

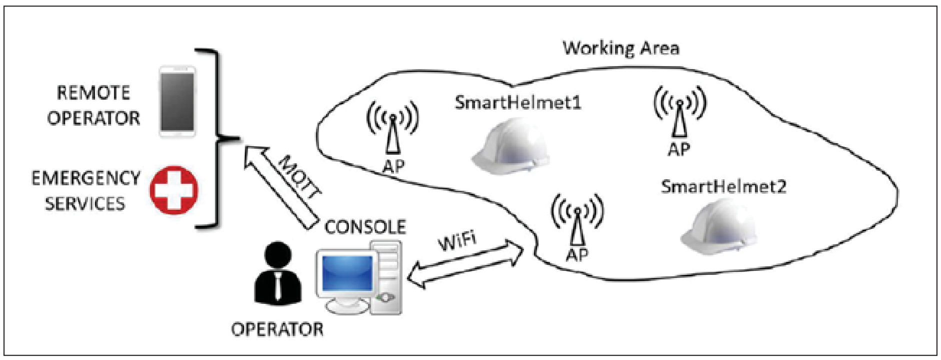

Figure 1.20 High-level description of the SAFE ecosystem
Taken from Altamura *et al.* (2019)

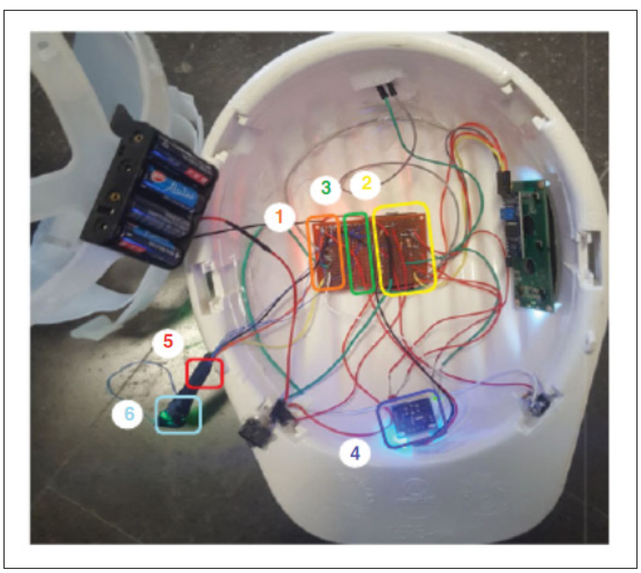

Figure 1.21 Six different components of SAFE prototype
Taken from Altamura *et al.* (2019)

The system included sensing capabilities such as an MQ-2 sensor, which is a sensitive quick flame detector able to reveal smoke in the air and flammable gases such as propane, hydrogen, alcohol, methane, and liquefied petroleum gas. The concentration of the gas within a predetermined range could be indicated by the detector. To monitor human physical measures of body temperature and heartbeat, an analog TMP sensor and PulseSensor were used.

The design was based on rapid prototyping techniques and used basic inexpensive modules and sensors. The sensors included a gas detector, temperature sensor, and heartbeat monitor that connected to the main MCU, an ATmega328P (Arduino Nano). The microcontroller could operate with low voltage. The working steps included a sensing section and a sense and communication interface. The microcontroller would gather data from sensors, make a 17-element data package and send it to the ESP8266 WiFi module. The proposed system had been prototyped in different implementation phases using a polyethylene safety hardhat as internal support for non-sensorial components, namely the battery pack, external slots for the gas sensor, communication buttons, power switch, a slot for the LCD, mobile support to place the temperature sensor, and the pulse sensor behind the ears (Altamura *et al.*, 2019).

A perspiration-measuring hardhat was developed by (Kosuda *et al.*, 2019). They attached four temperature and humidity sensors and calculated the amount of perspiration using the hardhat. The two sensors were attached to the two airflow entrances of the hardhat, and another two sensors and a fan were attached to the airflow output. They used WiFi to collect data. In their experiments, they found that it is possible to measure the amount of perspiration of the whole body only via this hardhat.

Dogbe *et al.* (2020) used shape-shifting technology to design a hardhat that protected workers' hearing from the loud noise that could damage the auditory system. As soon as the hardhat's sensor detected loud noise (exceeding a safe threshold), the microcontroller activated two servo motor-powered earmuffs to cover the ears.

Adjiski *et al.* (2019) attached sensors to the hardhat and safety glasses, provided communication with mobile phones and smartwatches, and the safety of workers improved (Figure 1.22). To do this, they attached specific sensors to the PPE clothes and, using an energy-efficient Bluetooth module, connected them to the smartwatches and smartphones. Regarding the architecting of the prototype, sensors collected data, and then this data was sent to the mobile phones by Bluetooth. The data was sent to the center as soon as there was a WiFi connection. By using this data, it was possible to provide different applications, such as a historical record of the site or controlling and predicting the risk of accidents and incidents on the site.

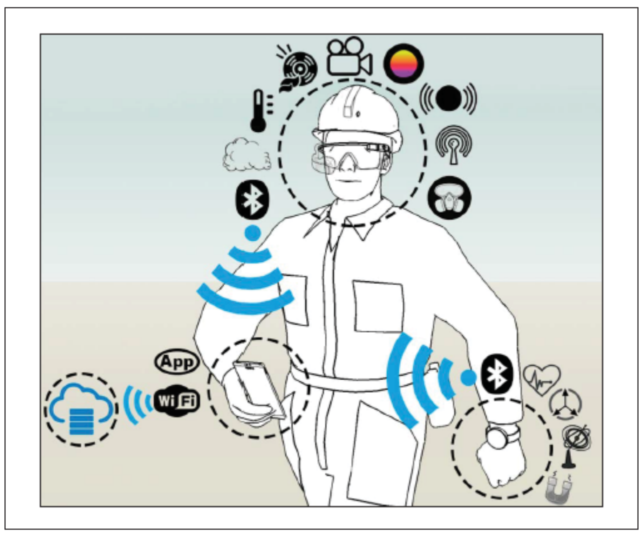

Figure 1.22 Overall prototype system
Taken from Adjiski *et al.* (2019)

Aliyev, Zhou, Hevesi, Hirsch & Lukowicz (2020) prototyped a hardhat with two purposes, worker's health and site monitoring. One of its main advantages was the flexibility of its hardware. The system had 10 different sensors with haptic feedback, and all hardware communication was achieved via Bluetooth. Furthermore, by developing a mobile application, it was possible to use the gathered data for future actions. The prototype could record worker motion activity, detect whether workers wore the hardhat correctly, monitor health signals such as temperature and pulse, notify workers by LED arrays in front of the workers' eyes, and use haptic feedback for more reliable notifications. To notify about the site the environment, certain sensors could detect parameters such as air pressure or gas resistance, etc. Also, this prototype could detect the object and obstacles around workers, and some sensors could detect UV exposure. Another function was a flashlight to see or read in the dark.

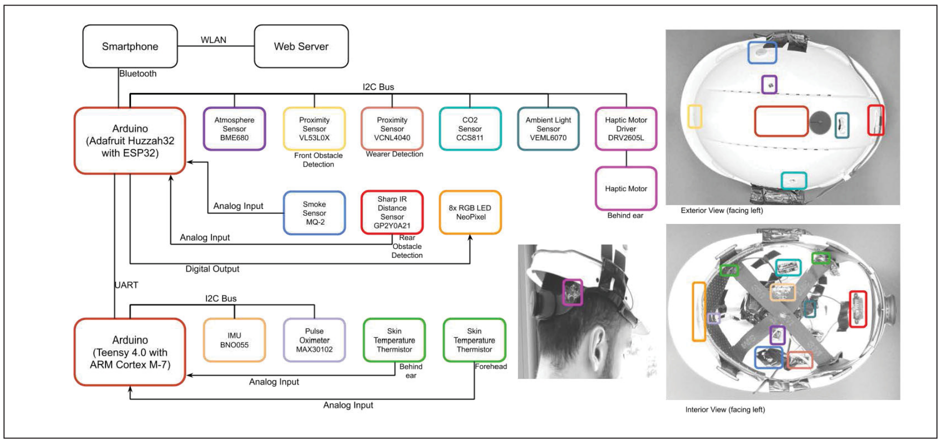

Figure 1.23 Overall prototype
Taken from Aliyev *et al.* (2020)

1.3.4.3 PPE and Wind

This Section qualitatively explores the potential of integrating wind detection and PPE, focusing particularly on hardhats. Wearable wind sensors and anemometers will be examined regarding the size of sensors and whether it is possible to attach them to PPE. It is important to note that we could not find any mention in the literature as to wind detection and PPE. For this Section, we decided to limit our research to studies that focus on small wind sensors or any type of small anemometers.

The development of a two-dimensional hot-air speed sensor based on micro-electromechanical technology was presented in (Zhou, 2019). The sensor operated in continuous power status and measured wind speed and direction using the thermal temperature differential approach. When the wind passed through the heater, the nearest section of the heater to the wind had a higher rate of temperature drop than the further section of the heater. Thus, wind speed and direction detection could be achieved by calculating the variation in temperature.

A glass was utilized with this sensor with low thermal conductivity to improve the sensor's performance by providing good thermal isolation. Regarding the fabrication, two thin pieces, titanium, and platinum were consigned to the glass.

An ANSYS simulation test was conducted with wind speeds between 2 and 10 m/s, and wind orientation 45 degrees; they found that by increasing the wind speed, the temperature of the chip decreased, and the accuracy of the chip was higher. During the prototype test through the wind tunnel, they found that their simulation result was correct when the wind speed was between 2.5 and 10 m/s for all orientations, and the error of the wind's direct detection was less than 8 degrees. Furthermore, the sensor had low energy efficiency but excellent sensitivity and a quick response time. One of the advantages of this thermo-differential sensor was that it could detect the direction of the wind and had a higher rate of sensitivity when the airflow was low. However, it did not work well in the high-speed wind.

To test the anemometer, they used a wind tunnel; when the wind speed changed from 0 to 10 m/s, the accuracy of the anemometer was the same as the simulation test results. However, at 10 m/s, the detection accuracy decreased as the temperature of the environment decreased. It is important to note that the sensor output voltage alternated between sine and cosine when the wind changed from constant and inconstant.

The development and testing of a low-cost micro-machined wind sensor with thermopiles based on the calorimetric principle were produced by (Zhu, Chen, Gu, Qin & Huang, 2014) on a two-dimensional ceramic substrate. The sensor prototype had two sides (Figure 1.24): one side to be exposed directly to the wind, and the other side was a nickel heater and nickel/aluminum thermopile on a ceramic piece.

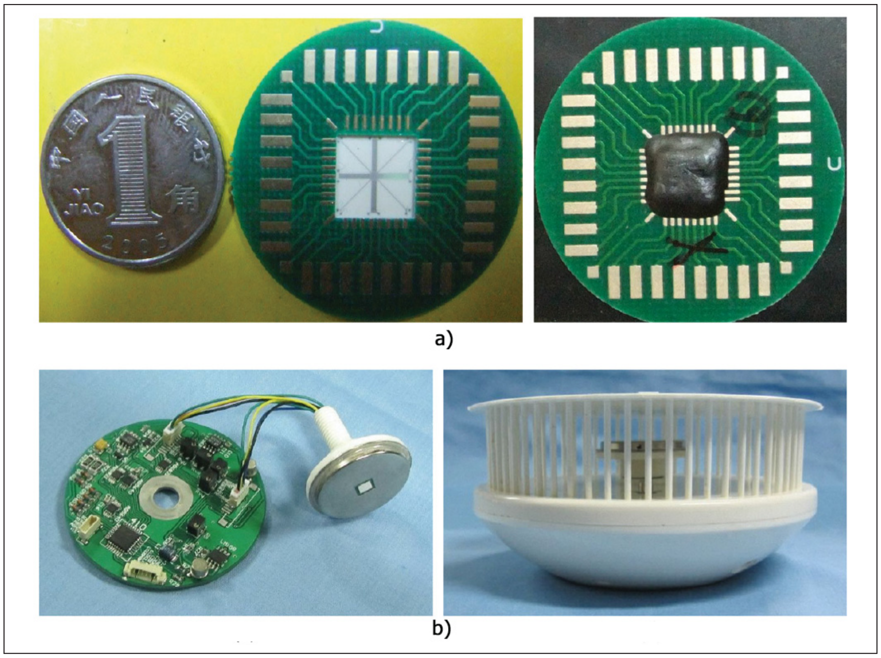

Figure 1.24 The design of sensor: a) process of bonding,
b) complete package in shell
Taken from Zhu *et al.* (2014)

The entire procedure was straightforward, and just three covers were required. This technology had a low manufacturing cost and reduced the variations produced by the chip-packaging process without the need for an additional packaging plate. Two different tests were run to improve the quality of the prototypes by simulation and analyzing the accuracy of the sensor by testing it in the wind tunnel. Unlike other thermosensitive thermal wind sensors directly produced on ceramic boards, this sensor used thermopiles as the sensing element to reduce the sensor's offset output caused by process error. Furthermore, in the simulation process, by analyzing the difference in temperature at various points on the substrate, a method was proposed to test the impact of "chip size, heater length, and heating power" on the effectiveness of the wind sensor, making it possible to optimize the cost of prototyping. Regarding the wind tunnel test, they found that the sensor could measure wind speed around 30 m/s and detect all 360 degrees of the wind direction. It is important to note that after a 2000-fold amplification, the output offset of the sensor was less than 0.1 mV in 300 K.

In Rehman, Mohandes & Alhems (2018) the effect of wind speed and its characteristics was studied for 8 months. They used a Lidar anemometer to measure parameters such as “wind speed, Weibull shape and scale parameters, wind power density; frequency, wind turbulence; wind shear exponent; a correlation between wind speeds at adjacent heights, the wind energy”. To gather related data, they used Laser Doppler (LiDAR) anemometry methods, which are more efficient because of various advantages, namely, this method and sensor did not have a high installation cost, there is no need for individual component measurement, nor is there a risk of measurement drift, small or no licensing requirements, no aircraft obstruction, less vulnerable to lightning, and the sensor was not impacted by frosting.

Cheng, Chang, Fu & Liu (2019) designed another type of anemometer that detected both wind speed and direction (see Figure 1.25). It consisted of two fiber Bragg gratings, a stainless-steel bar, and a plastic ball. The two fiber Bragg gratings (FBGs) were attached to the length of the stainless-steel rod with a 90-degree position separation.

As to its design, when the stainless steel received the wind, this triggered the FBGs, making it possible to detect the wind speed and direction by the different wavelength shifts. This prototype has two advantages: first, low production cost. Second, it could be used in different conditions and environments as the sensor works with two FBGs. From the results of the experiment, the anemometer’s wind speed accuracy was 0.49 m/s, and its responsivity was 0.02 nm/(m/s) with an error of 2.5%. Regarding the wind direction, the error of detection was about 0.70%.

1.3.4.4 Detection of Wind Speed and Direction

In this Section, we review the literature that presents studies closest to the objectives of the present research. In the first paper, the authors (Widyantara, Rivai & Purwanto, 2019) prototype a system to detect gas leakage using a mobile robot. The anemometer they used to detect the direction of the wind is "wind sensor Rev P5". The second work (Li, Zhao & Zhu, 2018) detected wind speed and direction by attaching a “thermal flow vector sensor” to the wristband. In that study, the sensors used to detect the wind speed and direction are different from those used in

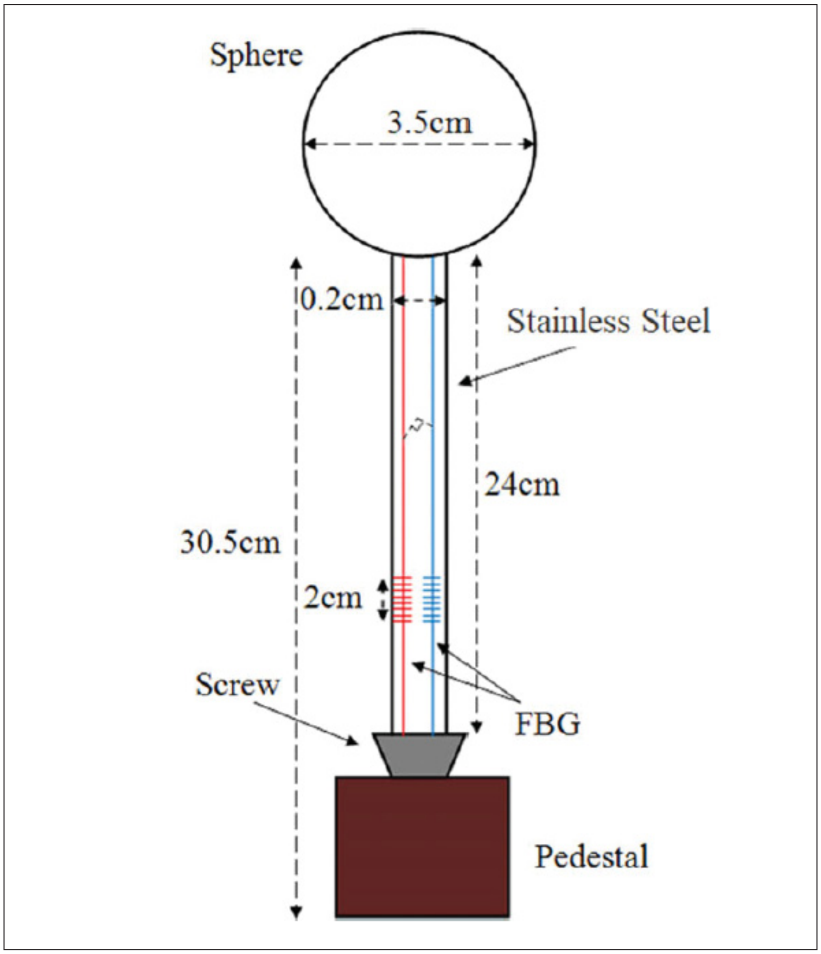

Figure 1.25 The design of the fiber anemometer
Taken from Cheng *et al.* (2019)

the previously-mentioned work, but they detected the same parameters of wind characteristics. We will now examine these two articles, explain the similarities and differences, and evaluate their relevance considering the objectives of our work.

Widyantara *et al.* (2019) designed a sensor system to detect the direction of the wind considering a positive temperature coefficient thermistor. The study utilized a thermal anemometer-based wind speed produced by Modern Device. The robot could detect the direction of the wind and track the odor plume might increase to 80% the efficacy of detection.

Thus, this prototype could be used for several applications and on different devices, for example, an odor tracking robot, gas leakage finder robot (Zhang, Li & Wang, 2012; Lu, 2013), or robots for tracking the source of the odor. The authors used three anemometers positioned at 120-degree angles measuring different directions (Figure 1.26). As a result, the 12 directions of wind were detected. This method can be applied in the context of our research, even if the objectives of this study are different from ours.

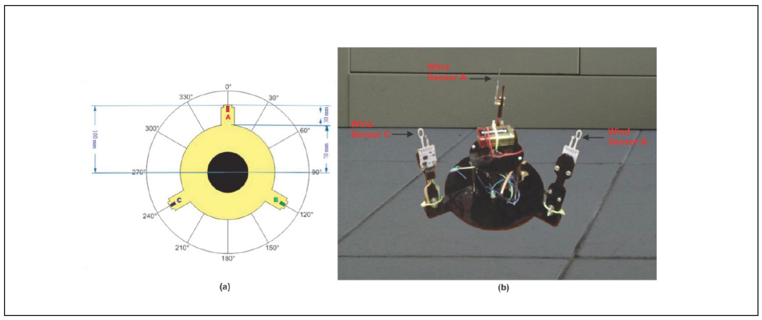

Figure 1.26   Wind sensor a) schema of design,
b) the mechanical design
Taken from Widyantara *et al.* (2019)

To determine the accuracy and characteristics of this anemometer, they ran an experiment in a small wind tunnel with a speed range of 0.22 to 3.1 m/s. Furthermore, they repeated the test at three different speeds and rotated the anemometers 30 degrees. The accuracy of the wind detection was 91.6%. To predict the wind direction, they applied a Multi-Layer Perceptron (MLP) neural network algorithm as it can solve not only linear problems but also multi-layer problems. These authors also ran an experiment in the open air to assess the accuracy of wind source detection when the anemometer is attached to a mobile robot. The accuracy of wind direction was between 75 and 87.5%.

A prototyped wearable anemometer was developed and designed by Li *et al.* (2018). The system had a "thermal flow vector sensor" to measure wind direction and speed. In our work, we used a sensor using an omnidirectional thermal anemometer. To make the thermal sensor, three circular Pt hot-film sensors equally spaced inside a circle were manufactured on a polyimide base.

It is important to note that two commercial triaxial micro accelerometers and triaxial micro magnetometers were used to assess wind orientation detection. The anemometer (Figure 1.27) had various components: a thermal flow vector sensor, a commercial micro accelerometer and magnetometer, a lithium battery, and a Bluetooth module.

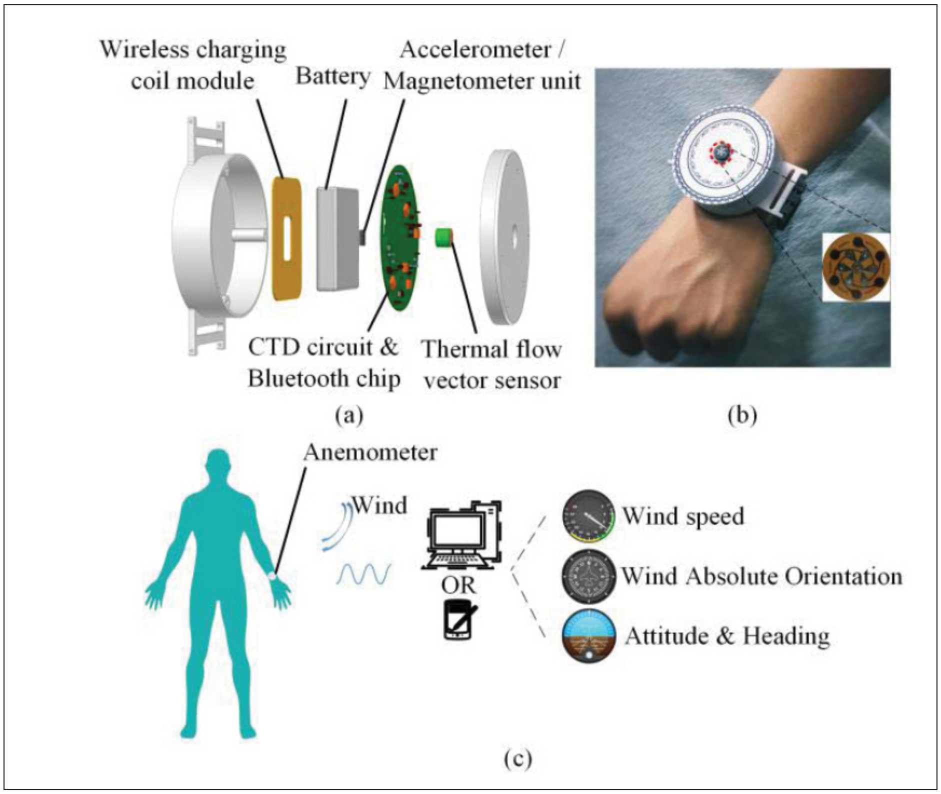

Figure 1.27 Anemometer design a) Hardware setup,
b) The anemometer, c) Practical diagram
Taken from Li *et al.* (2018)

As illustrated in Figure 1.28, to keep the thermal heat transfer constant and concentrically balanced, three-round components were arranged in a circular pattern. To measure stream temperature variations, the temperature sensor system was split into three discrete areas. Three thermometer sensors measured temperature fluctuations in the hot zone when they received wind, and this data was used to detect the wind speed ratio.

By obtaining the heating power of the three hot-films working in fixed temperature variation cycles, the flow sensor measured the speed and related angle. In addition, the ratio of the wind alerted the "wind absolute orientation in the geographic coordinate system."

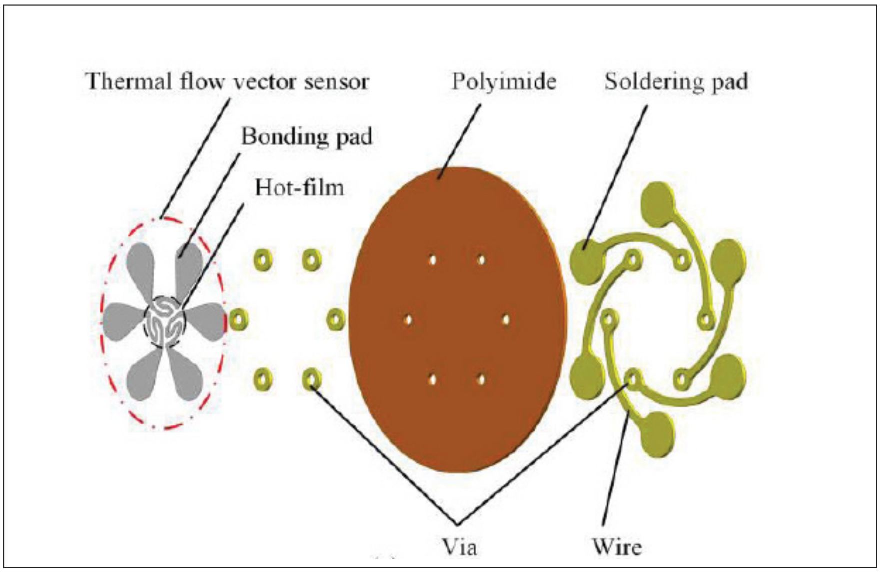

Figure 1.28 Design of the custom micro thermal flow vector sensor
Taken from Li *et al.* (2018)

As for data gathering, see Figure 1.29, the ADC converter could collect the data of the thermal flow sensor. The circuit connects the accelerometer and magnetometer to the microcontroller. All gathered data using a microcontroller was sent to the PC or smartphone via Bluetooth. The transmission rate was 50 frames per second. Under a wind speed of 0-20 m/s, the anemometer's power consumption was less than 500 mW. The anemometer could operate for a maximum of 4 hours using a 600 mAh lithium battery. Figure 1.30 presents the overall hardware and software prototype. This system shows wind direction, speed, and ratio.

Regarding the accuracy of wind speed detection, the root mean square (rms) error of the wind speed measurement were less than 0.2 m/s between 0 and 19 m/s, the rms errors of wind relative angle was less than 3 degrees, and absolute orientation was less than 4 degrees. Mostly this

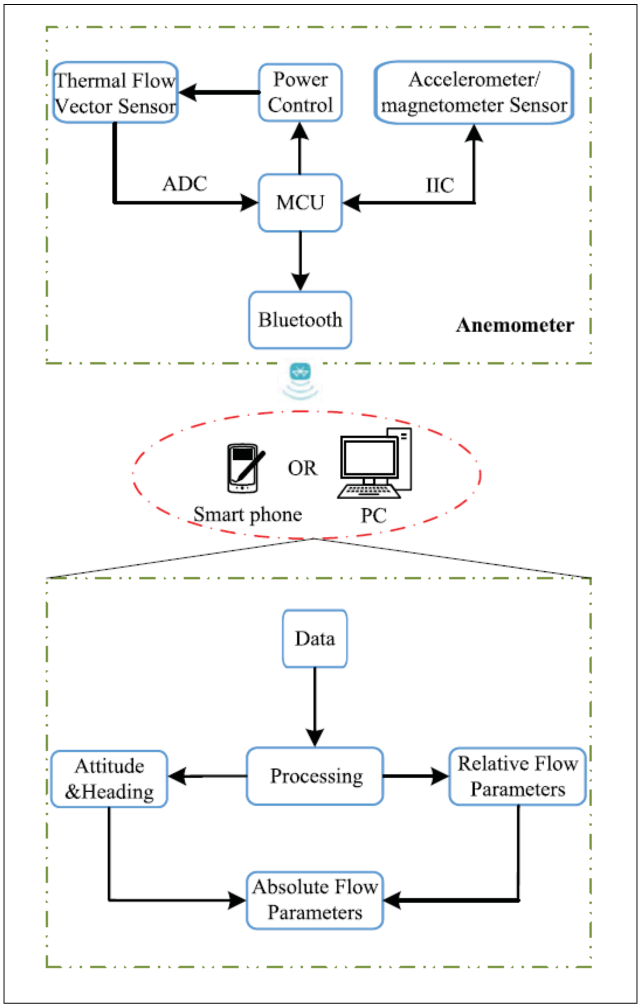

Figure 1.29 Data Diagram
Taken from Li *et al.* (2018)

anemometer is used to detect human motion and posture by calculating the received speed of human body motion while this anemometer is worn on the human arm.

1.4 Synthesis

This study inquires into the domain of smart PPE and wearable applications related to the effect of wind in construction to address the existing limitations. Literature from various areas such as safety on construction site, health monitoring, worker's fall detection, monitoring risk, and environmental conditions has been studied. Accordingly, existing limitations in safety,

Figure 1.30 Design of overall platform
and mobile application
Taken from Li *et al.* (2018)

technology insufficiency, and human error detection have been identified. More research is needed in this regard, and new approaches need to be developed.

Our overall project aims to utilize wearable sensors and IoT to detect wind speed and direction in construction sites, to propose potential improvements for workers' safety. Researchers have developed various smart PPEs or wearables using, for instance, a hardhat, gloves, and glasses. Nevertheless, studies indicated that traditional approaches are incapable of answering the needs for safety-related measures on construction sites completely. The root of the problem is that the current methods used to detect wind speeds and direction are often error-prone, fail to cover the entire construction site, or cannot transmit the information for potential danger in real-time.

We performed a Systematic Literature Review (SLR) to thoroughly review all the literature pertaining to wind, PPE, and construction safety. The 76 articles retained were investigated using scientometric analysis. A qualitative analysis was conducted to understand the methods for wind speed and direction detection using smart PPE or wearables for the construction industry, to extract the challenges, the gaps, and the limitations of the current solutions. This study aims to address them via implementing IoT-based wearable wind sensors.

Our literature and best practices review focused on three subcategories: First, determine the effect of wind on construction and workers' safety; secondly, identify how personal protective equipment (PPE) is employed and improved to boost the safety of workers and decrease the different types of accidents and incidents. Third, how wind detectors are being implemented on PPE.

From these three categories, we conclude that while there were many studies on the effects of weather on construction sites, few studies focused specifically on the effect of wind on this industry (in terms of safety). Our review revealed that few studies research the effect of wind in relation to accidents and incidents for workers in construction sites. Most papers focused on the damage of strong winds on structures, materials, and equipment. We also found that based on the previous studies (Jung, Park, Lee & Kim, 2016), the wind speed measured at ground level might be completely different from that at the higher floors of construction sites. This is why in this study, we decided to detect the wind characteristics for each worker. Thus, our prototype could measure the wind speed and direction in all the various site locations as the sensors detecting the wind characteristics would be attached to their hardhat. Although there are different studies on the effects of wind on construction projects, few focus on the impact of wind on workers (Schuldt *et al.*, 2021). There is a knowledge gap regarding the effect of wind and portable wind detectors.

From the second category, we found that most of the detection prototypes were attached to the hardhat and focused on adding technologies to make it smarter to improve the safety of laborers. In brief, the improvements provided by these prototypes were mostly related to human biometric signals, localization of workers on construction sites, management of proper hardhat wearing, detection of gas, improving workers' visibility by adding lights, obstacle detection, and the ability to declare an emergency either by the workers or site management. It is important to note that most of the studies focused on adding technology to the hardhat to improve the safety of workers with their prototypes. To the best of our knowledge, there does not appear to be a study on attaching a wind sensor to a hardhat or to any other type of PPE, which shows there is a knowledge gap on this topic and the need for future work.

From the third category, we reviewed the possible sensors that can be used to detect wind characteristics. There are various types of sensors. However, the thermal anemometer is the only sensor that can attach to a hardhat and, since we intend to use this type of wearable device for our final prototype, We plan to consider this anemometer for our proposed solution.

Finally, we focused on the two articles that were presented developments having some common characteristics with the objectives of our work. One of these studies used the same anemometer that we decided to add to our prototype, and from their study, we found that this anemometer could detect wind speed and direction. However, they used their prototype to improve gas detection and attached the anemometers to a mobile robot, which is different from our purpose. The second article designed a wristband that detects wind characteristics. We assume that attaching a wind sensor to a hardhat may be more effective because all workers must use a hardhat in construction sites. Moreover, the wristband might be covered by sleeves or another object, and as a result, the detection of wind direction and speed might be hindered.

In conclusion, we did not find any research or studies that implement a wearable wind sensor system to detect wind characteristics for safety issues. The objective of our work is to enable the detection of wind speed and direction in different locations of the construction site in real-time. This will help solve the problem of wind readings at ground level differing from those at the upper floors of a structure by collecting and modeling data received from each hardhat.

CHAPTER 2

RESEARCH METHODOLOGY AND PROPOSED SOLUTION

The main objective of this study is to improve workers' safety by proposing a new method to predict wind speed to avoid wind-related safety issues in construction sites. The main objective is divided into four sub-objectives as follows (as explained in Chapter 1):

1. To propose an IoT-based hardware solution to collect environmental information to be used for detecting wind speed and direction on the construction sites.
2. To investigate a hardware solution integrated in mandatory safety gears (i.e hardhat).
3. To investigate a method to accurately predict wind speed and direction using data collected from sensors using a supervised machine learning algorithm.
4. To design and implement a data collection station to create a dataset required for the machine learning models.

Design science research (DSR) methodology is employed in this study, which is commonly used in the field of information systems. Considering the fact that, this research intends to generate new knowledge by designing, developing and, evaluating a prototype, DSR methodology is considered suitable.

2.1 Design Science Research Methodology

The DSR is not a theoretical method, and it is ideal for creating artifacts to solve real-life problems (Hevner & Chatterjee, 2010). The DSR is relevant to the vast array of artifacts. "An artifact is an object that can be used to solve a practical problem by interacting with a context" (Johannesson & Perjons, 2014). Designing an artifact in DSR means building and evaluating something new. For example, an artifact could be a theoretical framework, complex system, hardware, software, or a human-computer interface.

According to Hevner and Chatterjee (2010), there are five phases in the design science methodology to follow during the design, implementation, and test process, namely: the problem awareness, suggestion, development, evaluation, and conclusion (as shown in Figure 2.1).

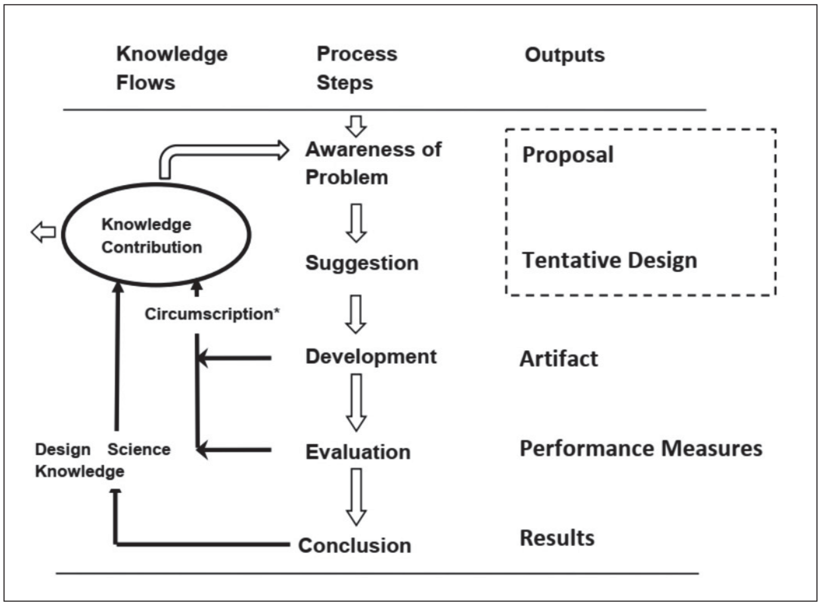

Figure 2.1 Design Science Research Methodology steps
Taken from Hevner & Chatterjee (2010)

In the context of this research, the practical problem addressed is the real-time detection of the safe/unsafe conditions in adverse weather (high-speed wind); and the proposed artifact is a wearable device (i.e., hardhat) equipped with four hot-wire sensors and emitting safety alerts related to dangerous wind speed and direction. The five steps of the DSR method are explained in more details in the following points.

2.1.1 Awareness of Problem

Since the construction sites are constantly changing, the wind profile can vary according to the shape of the site, and the wind speed and direction may vary in different locations of the site. Furthermore, the wind profile changes in different latitudes, longitudes, or elevations. For example, with an increase in elevation in high-rise buildings, the effect of weather conditions could be more intense (Jung *et al.*, 2016). Typically the weather information comes from a reliable meteorological website or a local weather station (placed in the construction site).

However, workers on construction sites may be exposed to the risks of high wind speeds while the reported wind speed for the site is within the acceptable range. Therefore, there is an inconsistency between the data obtained from a meteorological website or a local weather station and the actual wind speed in construction sites. Moreover, wind gust ("a sudden strong increase in the amount and speed of the wind that is blowing" [1]) is one of the main safety concerns related to the high wind speed. Therefore, to avoid the above-mentioned problem, wind speed and direction in various locations of the construction sites should be monitored regularly. The best solution is to measure the wind speed and direction in real-time for each worker independently, considering their working area.

2.1.2 Proposed Solution

Regarding the choice of wearable devices to host wind sensors, some devices such as smart wristbands, glasses, or jackets may be covered by workers' clothing or other objects, making the detection of wind speed and direction challenging. The best candidate is wearable gear that is continuously exposed to the wind profile. Hence, the hardhat is chosen since each worker on a construction site is required to wear it as part of the mandatory personal protective equipment. The idea of using a hardhat as a smart wearable device by adding a collection of electronic components has been successfully investigated in many research projects to correspond to various problems. Therefore, in this research, the use of a hardhat capable of measuring wind speed and direction for each worker is proposed. The proposed solution is elaborated in detail in Section 2.2.

2.1.3 Prototyping

The term "prototyping" refers to the process of developing an artifact. In this research, the prototype is a hardhat equipped with sensors and a software that can detect wind speed and direction in real-time to increase safety measures. The primary objective of designing a hardhat was to gather all the wind-related data using the attached sensors and send them to our software

[1] https://www.oxfordlearnersdictionaries.com/definition/english/gust_1

through a wireless connection. In addition, collecting real-time data from the hardhat and predicting wind speed and direction using a machine learning algorithm were the main steps of the prototyping process. Four hot-wire sensors were installed on the front, back, left, and right sides of the hardhat to collect airflow information. Furthermore, these sensors are connected to an Arduino board and a Bluetooth module to send and receive data wirelessly. This artifact serves as a proof of concept, demonstrating the feasibility of the proposed solution. Details of the prototype design and implementation is presented in Section 3.1.1.

2.1.4 Evaluation

The evaluation step aims to evaluate the designed prototype. This step offers feedback or guidelines to the two former steps (i.e., awareness of the problem and proposed solution), allowing for incremental and iterative advancement. The data from hardhat sensors needs to be collected to provide the required materials for the evaluation step. Hence,the methods and tools required for data collection and analysis were designed and implemented. Details of the evaluation is presented in Section 3.3.3.

2.1.4.1 Data Collection Method

The designed hardhat equipped with four hot-wire sensors were placed inside the wind tunnel (a part of our data collection station) to collect data regarding various wind speeds and directions. As a result, the raw data from hardhat's sensors and reference anemometer were collected to generate the dataset. Therefore, the dataset was made of the data gathered from sensors exposed to the wind at controlled speeds and directions.

2.1.4.2 Data Collection Tools

1. **Hardhat**

   To create the prototype hardhat, four hot-wire sensors were used as they are lightweight and small. Consequently, workers can comfortably wear the hardhat equipped with sensors. The sensors are capable of capturing a wide range of wind speeds. Additionally, the sensors can be used as an array to detect wind speed and direction. Details about the proposed solution is elaborated in Section 2.2.2.1.

2. **Data collection station**

   Our data collection station included a wind tunnel, reference anemometers, and a rotational platform. A constant wind speed is applied during each data collection step using the control panel of the wind tunnel. A reference anemometer is placed inside the wind tunnel, allowing to record the actual wind speed in real-time. To control the wind direction, a rotational platform is designed and implemented which allows various angles for our hardhat inside the wind tunnel. To place the hardhat inside the data collection station a mannequin head is attached the developed rotational platform. Details about the data collection station is elaborated in Section 3.1.2.

2.1.4.3 Data Analysis Method

After gathering data from the sensors and the data collection station, they are organized into two categories. The first category was the data from the hot-wire sensors attached to the hardhat, and the second category was the data from the reference anemometer and the rotational platform (i.e., the data related to wind exposure direction). The goal of the prediction algorithm is to find patterns or correlations between these two categories. Therefore, the collected data from hardhat sensors, rotational platform, and reference anemometer were considered as an input of the machine learning algorithm. Details of the proposed data prediction method is elaborated in Section 3.3.

2.1.4.4 Data Analysis Tools

Machine learning is essentially the use of data rather than logic by a machine to execute tasks (Yadav & Shukla, 2016). The goal of a machine learning algorithm is to create a model that generalizes to out-of-sample data. Additionally, evaluation is a critical component of any machine learning model, which estimates how well a given model performs on out-of-sample data (Na, 2017; Yadav & Shukla, 2016). In this research, ML.NET is used, which is a free machine learning library for the C# and F# programming languages that also supports Python models when used together with NimbusML (Na, 2018). Moreover, ML.NET provides the evaluation methods to measure various metrics for the trained model. The evaluation methods generate statistical measures depending on the machine learning task. Details of the evaluation methods is elaborated in Section 3.3.

2.1.5 Conclusion

The primary artifact of this study was our prototyped hardhat. The hardhat was equipped with four hot-wire sensors to detect real-time wind speed and direction. The proposed solution can improve safety via detecting wind characteristics in real-time and based on the position of each worker. Furthermore, the prototype's accuracy is evaluated by testing it in a wind tunnel. Using the IoT equipped hardhat, together with the developed data collection station, data from hardhat sensors is gathered to enable machine learning models. Finally, to test the developed models, various metrics related to our machine learning algorithm are used.

To conduct the first stage of our DSR, (i.e., awareness of the problem), a systematic literature review is conducted, which focuses on the state-of-the-art, current research gaps, and limitations. For the second stage, a solution is proposed. We concluded that the hardhat is the best option to host measuring sensors. Finally, a prototype (i.e., artifact) is designed and developed based on our proposed solution, which verifies the proposed solution. To complete the fourth stage, machine learning models were designed and trained using a gathered dataset. Finally, according to the data collection and evaluation phase, we determine that the artifact is adequately functioning.

2.2 Proposed Solution

This research proposes a solution for real-time monitoring of wind speed and direction, using hot-wire wind sensors attached to a hardhat, and a supervised machine learning algorithm that predicts the actual wind speed based on the sensor's readings. The main contributing elements for the realization of the system are: (1) hot-wire sensors to collect airflow data, (2) a wind tunnel and an accurate anemometers to generate wind and to record wind speed as a reference data for the dataset creation, (3) a rotational platform (which offers an effective solution to provide various angles for the hardware prototype to collect hot-wire sensors data), (4) a developed software application to control sensors and the rotational platform and to collect sensors' data and process them, and (5) a developed regression algorithm (a supervised machine learning algorithm) to predict the values for wind speed and direction. Figure 2.2 shows the main elements of the proposed solution. Each hardhat send its data (i.e., the data related to four hot-wire sensors) to the developed software wirelessly. The data collected from sensors, is used as an input of machine learning (ML) prediction models to predict the wind speed and direction. The machine learning models perform prediction using a gathered dataset. Finally, the software compares the wind speed with the reference values, send alerts to the workers or security agents, if the wind speed is beyond a set range.

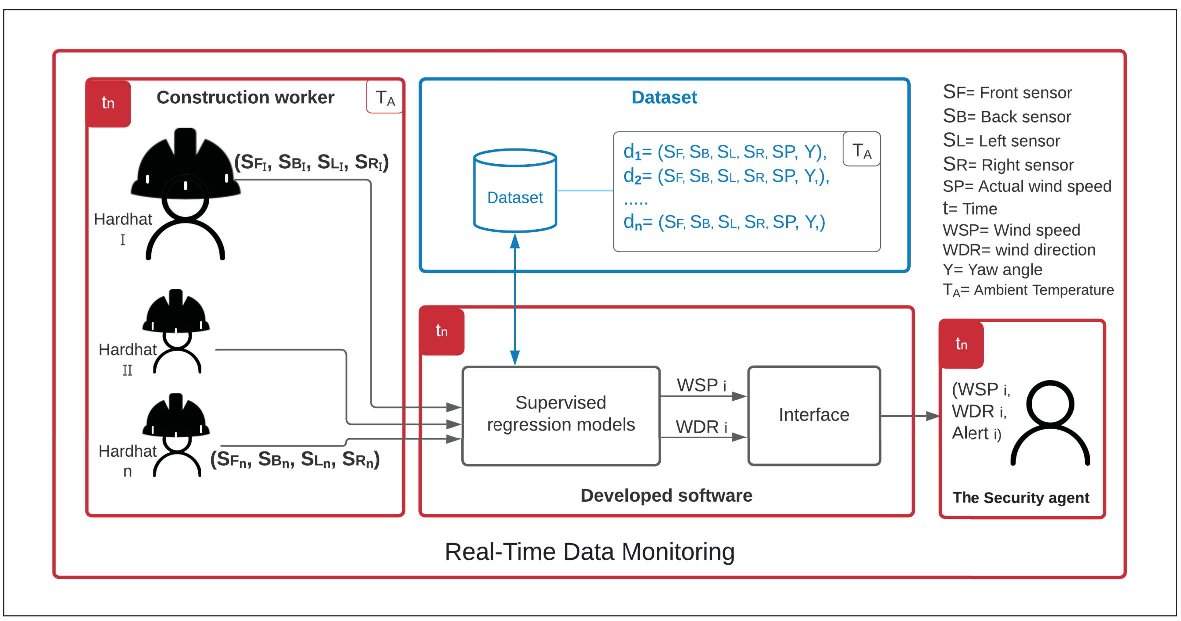

Figure 2.2 Proposed solution

2.2.1 Input Data

The main input of the proposed system is the data collected from sensors attached to the designed hardhat. The data from the hardhat consists of the readings from four hot-wire sensors. The raw data collected from sensors are inputs to the developed supervised ML algorithm, which allows predicting the wind speed and direction. For the machine learning algorithm to work, a robust data collection station is designed and implemented to collect data for creating the ML dataset. Details of the created dataset is presented in Section 3.2.3.

2.2.2 Hardware Concept

The proposed solution generates two variables as outputs which are real-time wind speed and direction. For that, the solution uses a wearable hardware (i.e., hardhat), which is part of personal safety equipment, equipped with sensors, processors, and communications modules. In this research, two sets of hardware setups need to be developed, tested, and verified: (1) hardhat equipped with sensors and other required electronic elements (Section 2.2.2.1); (2) data collection station (DCS) for acquiring dataset to be fed into the supervised ML algorithm. The DCS contains a wind tunnel, rotational platform, and a reference anemometer (Section 2.2.2.2). The limitation of the wind tunnel in generating a directional profile of wind was addressed by the design and implementation of the rotational platform.

2.2.2.1 Hardhat

The hardhat is chosen as a host device for the sensors. The hardhat is usually at the highest point of the body and is suitable for hosting wind sensors, as it is typically exposed to direct wind. In our proposed solution, the hardhat is equipped with four hot-wire sensors that are installed and arranged around it (Figure 2.3). The sensors are connected to an Arduino board, which is connected to a Bluetooth module. After receiving data from the sensors, the Bluetooth module sends them to the receiver, which is a computer that runs the software, wirelessly.

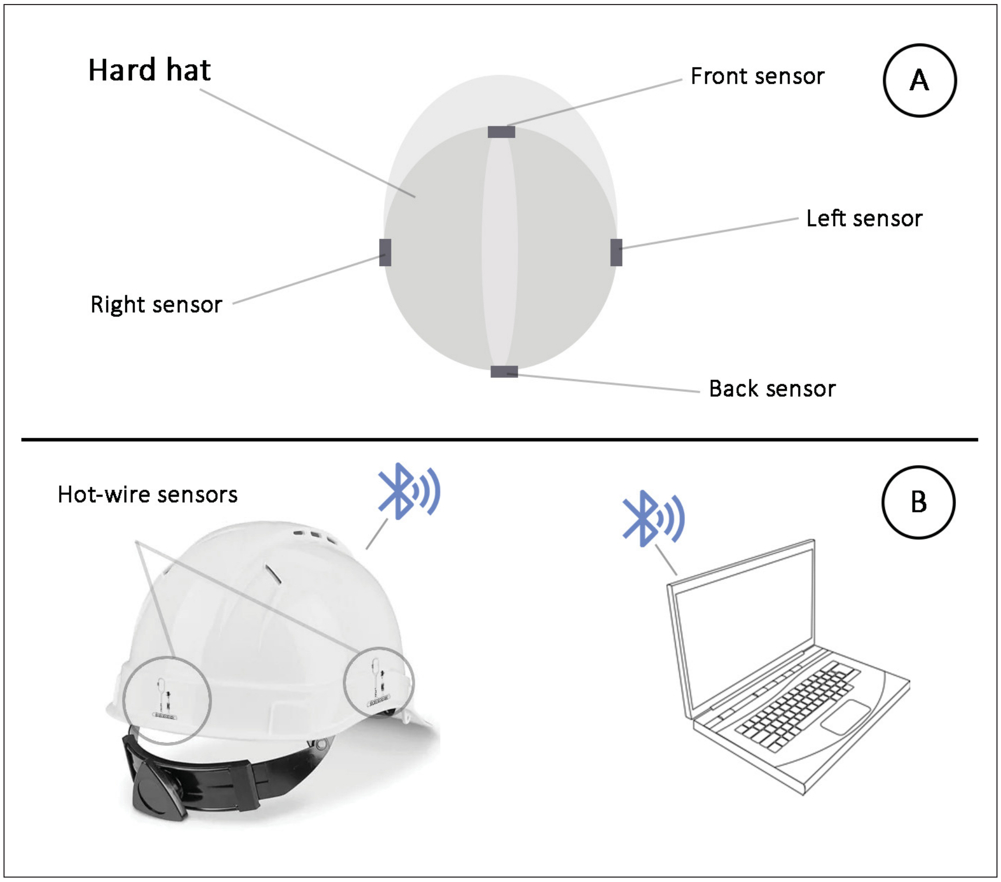

Figure 2.3 (a) Placement of hot-wire sensors on the hardhat
(b) Communication between sensors and the software

2.2.2.2 Data Collection Station

Data collection station is used to provide various wind speeds and directions for the purpose of dataset creation, testing, and evaluation of the proposed solution. To create the dataset, a controlled environment in which all the variables were accurately measurable is used. The data collecting station included a wind tunnel, reference anemometers, and a rotational platform that hosts the hardhat. Data collection station is used to measure and record required variables including, the current wind speed, the temperature of the test area, the wind exposure direction, and the data coming from hot-wire sensors (hardhat sensors) that are placed inside of it (Figure 2.4). The main elements of the data collection station are explained as follows:

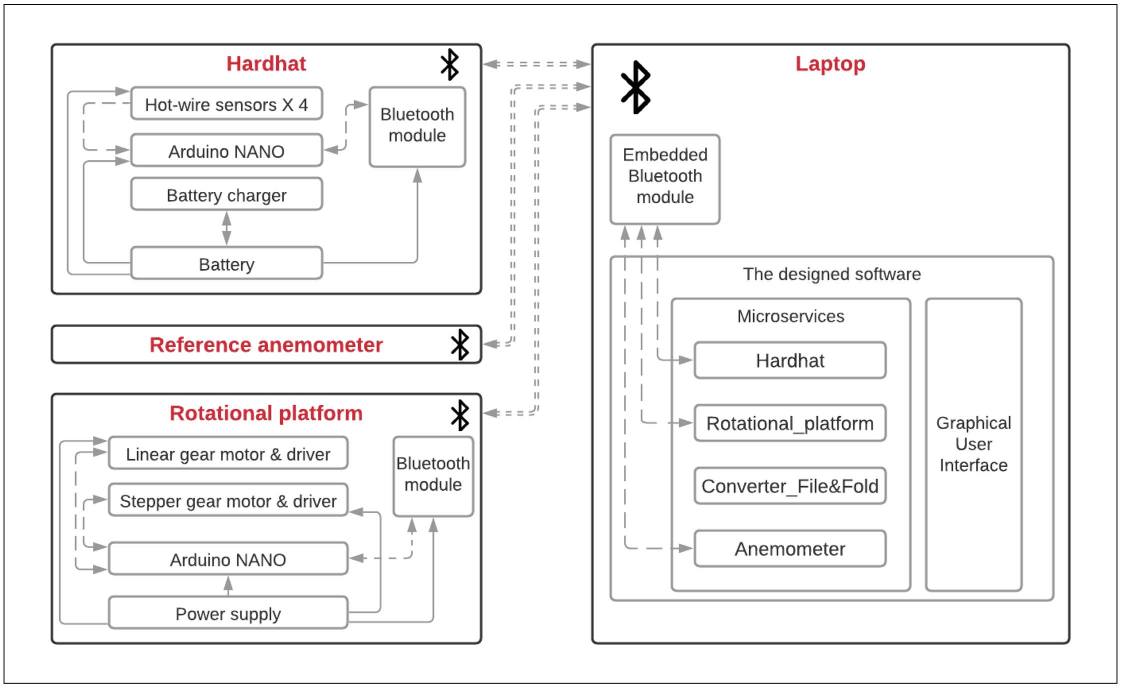

Figure 2.4 The data collection components

Wind Tunnel

Wind tunnel is the main element of our data collection station. It is used to prepare various wind speeds for the data collection and testing purposes. To evaluate the developed solution, the hardhat needs to be exposed to various wind speeds and directions and, additionally, data collection should be performed to make a dataset to be used in our machine learning models. The diameter of the cylindrical shape of the wind tunnel test area used in our research is 1.3m and with a length of 1.2 m. The prototype can be easily fit inside the wind tunnel as the entrance for the test area is 90 cm*85 cm. The wind tunnel can generate wind with speeds ranging from 3.5 to 11.5 m/s. In this research, a large wind tunnel is used, which can generate high wind speed as most of the small wind tunnels produced airflow of less than 5.0 m/s.

Reference Anemometer

Reference anemometer is one of the main components of DCS. It measures the actual wind speed inside the test area of the wind tunnel, which is one of the main inputs for creating the dataset. The amount of airflow generated by the wind tunnel is controlled by the wind tunnel panel. The reference anemometer measures the actual airflow to help adjust the wind speed to the desired value. On the other hand, it is common that even when a certain wind speed value is set for the wind tunnel, the speed changes over time. Consequently, the wind speed is required to be continually monitored to make sure that the right wind speed is maintained over time. In our prototype implementation, a secondary wireless reference anemometer is used to be able send data (i.e., wind speed and ambient temperature) via Bluetooth connection to the processing software.

Rotational Platform

Two variables (i.e., wind speed and direction) are needed for creating the dataset of the machine learning models. The wind speed is controlled via a wind tunnel panel, and the accurate value of the wind speed is provided by the reference anemometer placed inside the tunnel. As wind tunnels generally generate airflow in a single direction, to be able to expose the hardhat to various wind direction angles, a rotational platform, which hosts the hardhat inside the tunnel, is required (Figure 2.5). In this study, a rotational platform is developed that provides the possibility of rotating the hardhat to different angles inside the wind tunnel. The details of the prototype rotational platform are provided in Section 3.1.2.1.

2.2.3 Software Architecture and Implementation

In our proposed solution, the development of a software is required with the following requirements: (1) controlling the yaw and pitch of the rotational platform, (2) gathering data from hardhat sensors and controllers (such as hot-wire sensors, battery status, and etc.), (3) data collection from the reference anemometer, (4) data preparation for creating the machine learning models, and (5) creating a machine learning models to predict wind speed and direction based on input data from the hardhat's sensors.

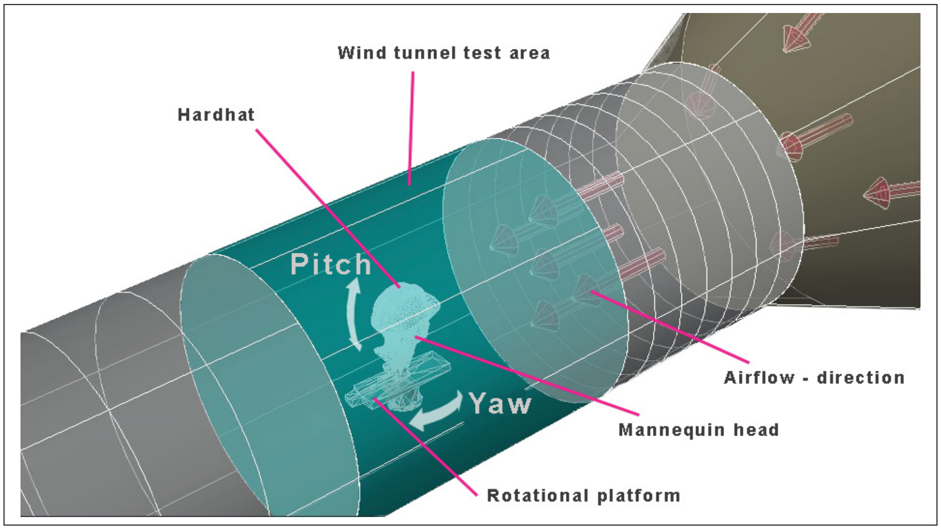

Figure 2.5 Data collection station

2.2.3.1 Software Architecture

The microservices architecture is proposed in this study, allowing for faster deployment and better scalability. Figure 2.6 illustrates the proposed service components and their relations. Five micro services are proposed, implemented and developed in this study: ML.NET service component, Converter service component, Hardhat service component, Rational platform service component, and Anemometer service component. The details of the micro services are provided in Section 2.2.3.2.

2.2.3.2 UML Diagrams

Figure 2.7 illustrates the UML class diagram of the proposed software to manage the system. This software consists of five separate dependencies. The composition relates three parts of the software, and aggregation relates the rest.

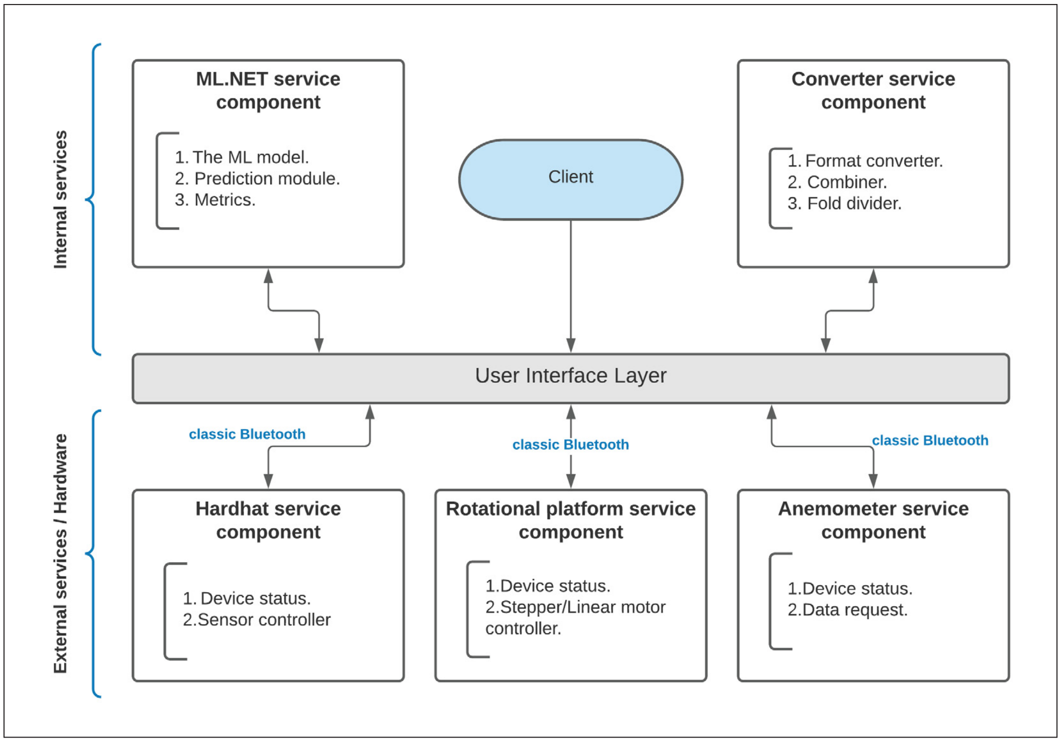

Figure 2.6 Main software microservice architecture

Composition Dependency

1. **Hardhat Service Component:** There are eight attributes and four main methods in this class. Controlling the connection status, turning on and off the sensors of the hardhat, and requesting data from the sensors are tasks related to this class.

2. **Rotational Platform Service Component:** This class includes seven attributes and six methods. It includes tasks such as checking the connection status, requesting the angular position of the stepper and linear motors, turning on and off each motor separately, and sending the command to set a new position for each motor individually.

3. **Anemometer Service Component:** This class consists of two attributes and four methods. These methods include controlling the hardware module's connection status, recording wind speed and ambient temperature, and checking the battery charge status.

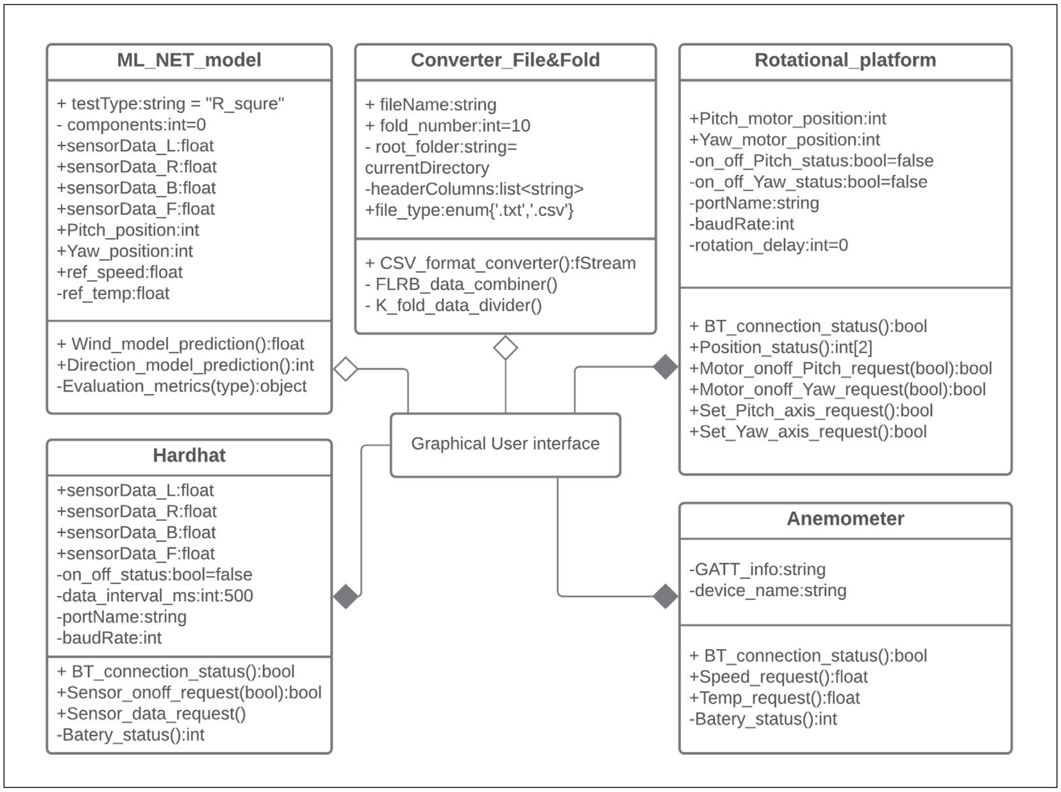

Figure 2.7 UML class diagram

Aggregation Dependency

1. **File and Fold Converter:** This class has six attributes and three methods. This class can convert files between different formats, prepare the machine learning model's required format, and arrange all folds for the cross-validation test.

2. **ML.NET Model:** For this class, there are ten attributes. This class can create the desired machine learning models and prepare them to predict wind speed and direction using a file with a defined format. This class includes three methods: first and second methods can predict wind speed and direction, while the third method is intended to evaluate different metrics on our machine learning models.

2.2.3.3 Software Verification

There are three main requirements for the software: the hardware controller for data gathering, the data converter to prepare the dataset, and the machine learning model for prediction. Therefore, the software should provide functionalities to correspond to the requirements. Verifying the functionalities of the software against the requirements, ensure that the developed software serves the needs.

The first requirement is related to the data gathering process. The software has a module that communicates to the hardware via a Bluetooth connection. The software sends and receives data from/to the hardhat prototype and the rotational platform via this module. The Bluetooth communication allows having access to the data of each hot-wire sensors, wirelessly. In addition, it allows to individually turn on and off the sensors. Furthermore, the platform rotates automatically in the transverse and vertical axis to change the wind direction exposure during the data collection process.

The second requirement is related to the collection of data for the machine learning models. The software gathers data from four hot-wire sensors, a reference anemometer, and transverse and vertical axis data related to the rotational platform and convert and assemble them into a single file.

The third requirement is the implementation of the machine learning models. After gathering all the data into a dataset, it is used to train the machine learning models. The software is capable to use the dataset for the supervised machine learning module and predict the wind speed and direction.

2.2.4 System Implementation Requirements

In order to implement a prototype of the proposed system, first, the required hardware and software needs to be designed and implemented. Second, a dataset needs to be gathered to be used to train the ML models. Finally, the system needs to be tested and verified.

Hardware and Software Preparation: The first hardware component is the hardhat. The hardhat needs to be equipped with sensors, processing unit, power source, and the communication module. Additionally, it has to be comfortable and secure to be used by the worker. The second component is the data collection station used for the data gathering and testing purposes. The data collection station contains a wind tunnel and reference anemometer. Additionally, to provide various wind directions for the hardhat during the data gathering and test process, a rotational platform for rotating the hardhat inside the wind tunnel and exposing it to the wind at different angles is required. A software needs to be designed and implemented that controls all the hardware components (the hardhat sensors, the rotational platform) in real-time.

Additionally, for the data collection and validation, a software is required to collect all the data from each sensor on the hardhat and at the specific speed of the wind, ambient temperature, and transverse and vertical axis. Details of the requirements of the software were explained in Section 2.2.3.3.

Data Gathering and Validation: After desiging and development of the hardware and the software, the following steps need to be taken: (1) data collection station preparation (i.e., preparation of hardware, software, and the tests area), (2) the preparation of data gathering plan, (3) data gathering, and (4) data validation.

Summary

In this Section, the proposed solution together with explanation about the prototype was discussed. The main component of the proposed solution was a hardhat equipped with four hot-wire sensors. Additionally, details about the proposed solution for the data collection station to create the dataset to be fed into the machine learning models is presented. Moreover, the software architecture and its implementation requirements was elaborated in this Section.

CHAPTER 3

PROTOTYPE IMPLEMENTATION

This Section provides details about the implementation of the prototype of the proposed system. This chapter is divided into four main sections. Section 3.1 presents a description of hardhat components and data collection station. Section 3.2 describes data set gathering. Section 3.3 explains how we build the machine learning models, collect metrics, and measure the performance of the models. Finally, Section 3.4 addresses the limitation, challenges and improvement scenarios.

3.1 Hardware Implementation

This Section provides details about the implementation of the prototype of the proposed system. It is divided into three main sections. Section 3.1.1 presents a description of hardhat components. Section 3.1.2 describes various parts of the data collection station. Finally, Section 3.1.3 addresses the implementation of the data collection station.

3.1.1 Hardhat

The hardhat prototype consists of the following modules: (1) hot-wire wind detection sensors, (2) Arduino board, (3) Bluetooth module, (4) DC-to-DC converter module, (5) battery, and (6) charger module (Figure 3.1). Details of each module are explained in the following subsections.

3.1.1.1 Hot-wire Sensor

Hot-wire sensor[1] (Figure 3.2) is a module that could measure the airflow rate. There are various types of anemometers based on their working principle. The hot-wire sensors used in this study are commonly used in a wide range of applications such as robot navigation, and drones. In this type of anemometer, the cooling effect is induced when air passes through the wire or

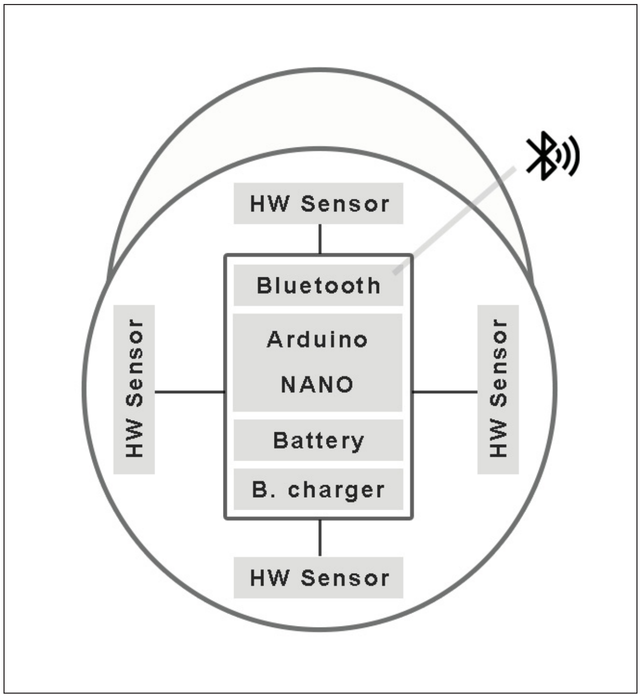

Figure 3.1 Hardhat overview

transducer's face of the anemometer (Chen, Zhu, Yi, Qin & Huang, 2015) and then the varying temperature magnitudes are transformed into a voltage. In comparison to other technologies, the thermal anemometer offers high accuracy. As a result, it's widely employed in turbulent wind analysis (Widyantara *et al.*, 2019).

Four hot-wire sensors are used as an array to measure the value of airflow exposed to the hardhat from different angles to calculate the actual wind speed and direction in the environment with the help of a machine learning algorithm. Each of these sensors is connected to the Arduino board separately. The data received from these sensors are analog. The Arduino board converts the analog input to digital using analog to digital converter units.

[1] https://moderndevice.com/product/wind-sensor-rev-p/

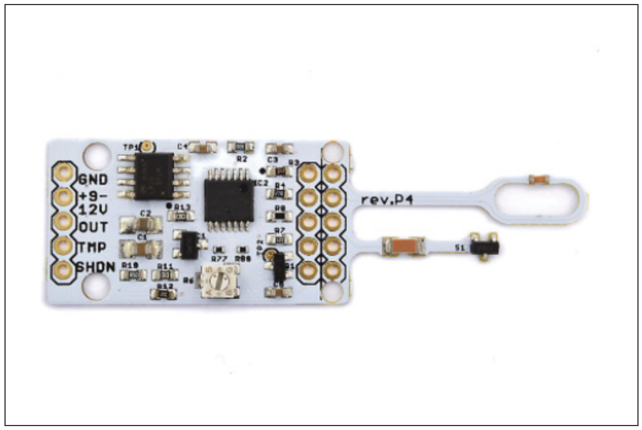

Figure 3.2   Wind Sensor Rev.P

In order to use this type of sensor, various tests were designed and conducted to assess the accuracy, consistency, and the influence of wind angle on the sensors. To perform the tests, a small open-return wind tunnel (Appendix II, Figure-A II-1) was designed. Appendix II, Table-A I-2 shows the specification of our designed wind tunnel. For the accuracy test, a conversion equation (provided by the manufacturer) was used to convert the output voltages from the sensor to the wind speed. In order to examine the accuracy of the sensors, the calculated wind speed was compared with the values obtained from reference wind speed data collected from an accurate anemometer (Appendix II, Figure-A II-2). For this purpose, the hot-wire sensor is connected to an Arduino board to collect the data (Appendix II, Figure-A II-3). Meanwhile, the wind speed data from the reference anemometer is collected to be compared with the output data of the hot-wire sensor.

Several tests were performed with different wind speeds (according to the speed range of the small wind tunnel). The duration of each test was 60 minutes. The results show that the hot-wire sensor could measure the wind speed as accurately as our reference anemometer, while the wind speed was between 0.1 to 5.0 m/s.

Regarding the consistency of readings, the same test was performed for a more extended period. In this test, the readings were collected for seven hours to see the possible changes in reading during the test. The results show that the readings from the hot-wire sensor were consistent.

In terms of the effects of wind angle on sensors' accuracy, four different tests were conducted. The hot-wire sensor was placed inside the small wind tunnel with a constant value of wind speed and a specific angle. The test was repeated four times with the same wind speed with four different angles (Appendix II, Figure-A II-4) in four separate tests. The data was recorded with the interval of one sample per second from hot-wire sensor for 60 minutes during each test. The results show that the hot-wire sensor is directional, due to the change of reading while the sensor is rotated inside the wind tunnel (Appendix II, Figure-A II-5).

3.1.1.2 Arduino Board

Arduino is an open-source platform that is widely used for various applications in the industry and academia. The basis of Arduino coding is the C/C++ programming language. Electronic projects can be put into operation more quickly with the help of the Arduino board.

Since multiple electronic components needed to be controlled by a main-board in our proposed solution, the Arduino board was chosen as it is powerful and easy to use. The following electronic components are connected to the Arduino board: (1) hot-wire wind detection sensor, (2) Bluetooth communication module, (3) DC-to-DC converter module, and (4) charger module. Figure 3.3 shows how the hot-wire sensors are connected to the Arduino board.

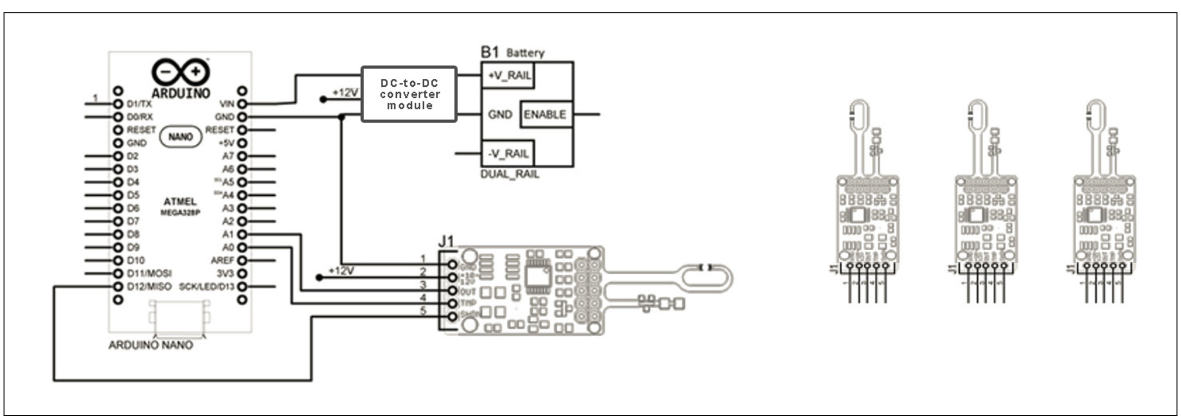

Figure 3.3 Hot-wire sensor schematic diagram

3.1.1.3 Bluetooth Module

Bluetooth is a short-range wireless technology for exchanging data. For the developed prototype, the HC-05 Bluetooth module is used. It is a simple Bluetooth Serial Port Protocol (SPP) module for setting up a transparent wireless serial connection. The HC-05 Bluetooth module can function either as a master or a slave. After connecting to the Arduino board, the Bluetooth module can wirelessly send the received data obtained from four hot-wire sensors to the control software.

3.1.1.4 DC-to-DC Converter Module

A DC-to-DC converter module is used to change the voltage. Since the hot-wire sensors operate at 12 V and the nominal voltage of lithium batteries is 3.7 V, a voltage converter was required. This DC-to-DC converter module provides the proper voltage and current for all hot-wire sensors.

3.1.1.5 Battery and Charger Module

The prototype uses a lithium battery with a nominal voltage of 3.7 V and a current of 1000 mA. The small size and weight of this battery make it suitable to be used for the prototype. In addition, the battery is charged with a battery charger module. This module has a micro USB port, allowing the prototype to be charged using a phone charger cable.

3.1.1.6 Assembled Prototype - Hardhat

After completing the circuit design and assembling the modules on the designed board, all the components are placed inside the hardhat. To do so, 3D-printed box is designed for the board and its modules allowing everything to fit inside. The sensors are then connected to four sides of the hardhat. Finally, the designed box is fixed inside the hardhat. Figure 3.4 (A) and (B) show the front and back side of the designed board, (C) shows how the box is placed inside the hardhat, and (D) is the final design.

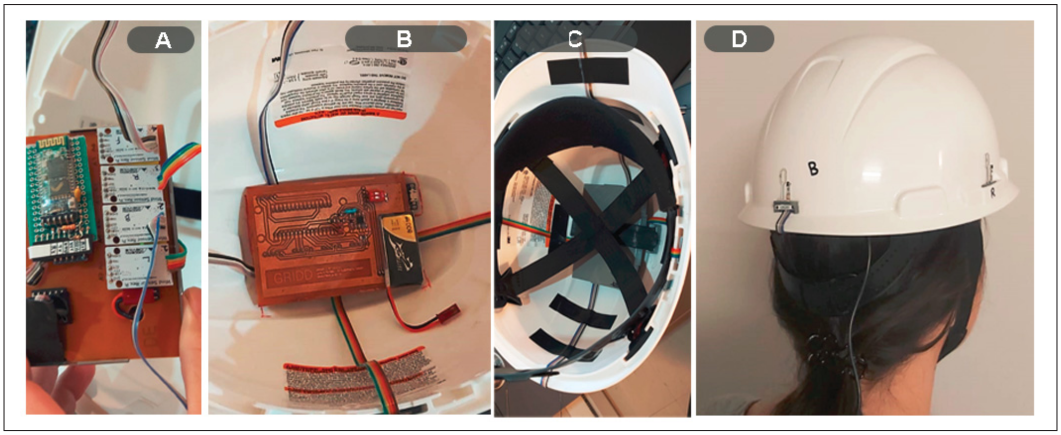

Figure 3.4 Prototype hardhat

3.1.2 Data Collection Station

In this Section, the hardware design and implementation of the data collection station are described. The rotational platform is discussed in Section 3.1.2.1. The platform is used to rotate the hardhat prototype on the transverse and vertical axis. Additionally, the general specifications of the wind tunnel are provided in Section 3.1.2.2. Finally, Section 3.1.2.3 explains the reference anemometer. The data gathered from the reference anemometer was one of the key items in the dataset.

3.1.2.1 Rotational Platform

The main element of the rotating platform prototype is illustrated in (Figure 3.5). The prototype includes an Arduino board, Bluetooth module, stepper motor and driver board, linear motor and driver board, and high amp power supply.

This prototype has two main types of mechanical movements: the transverse axis and the vertical axis rotation. The transverse axis is rotated by a linear motor, while a stepper motor rotates the vertical axis. Figure 3.6 shows how the prototype rotates on each axis.

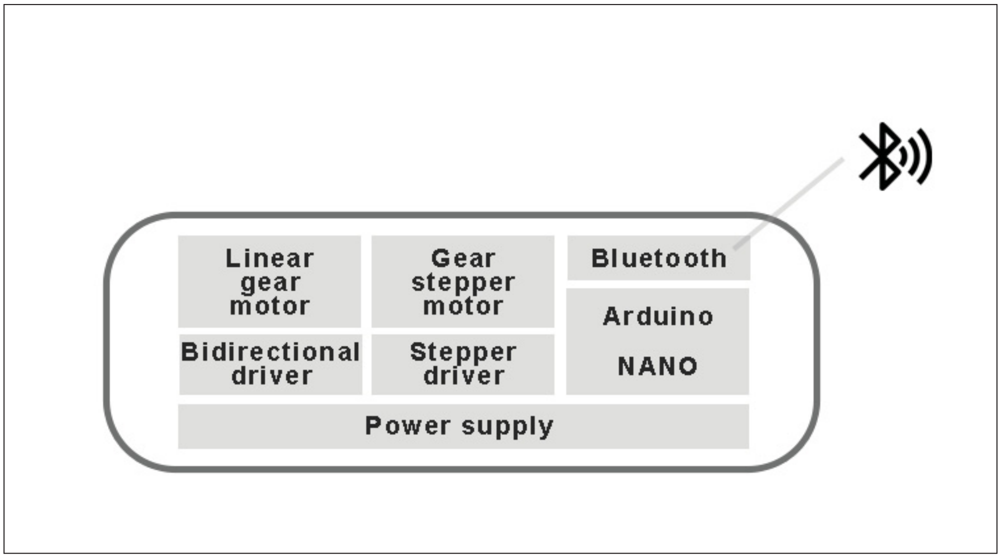

Figure 3.5 Main components of the rotational platform

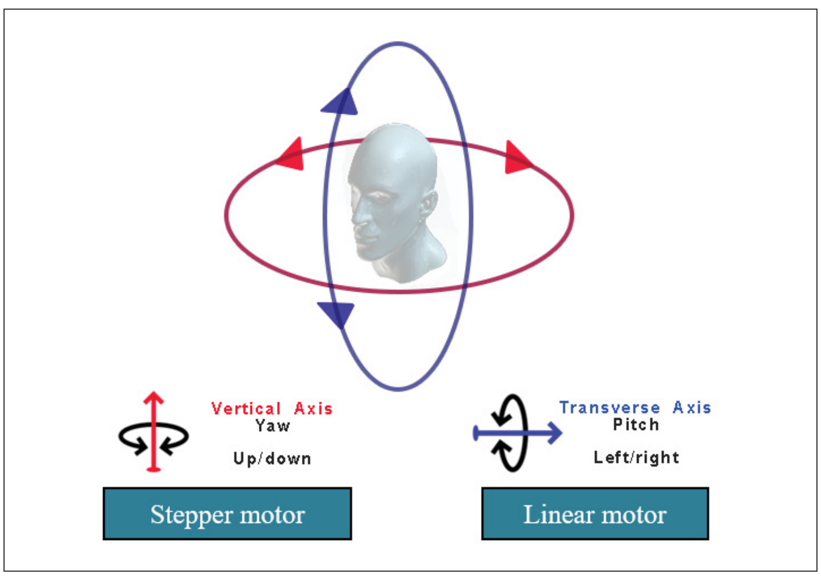

Figure 3.6 Types of motorized rotation

1. **Ardoino Board**

   Arduino board is used to control the rotational platform. It can control the stepper and the bidirectional driver and thus control the stepper and linear motor. Figure 3.7 shows the hardware connection diagram.

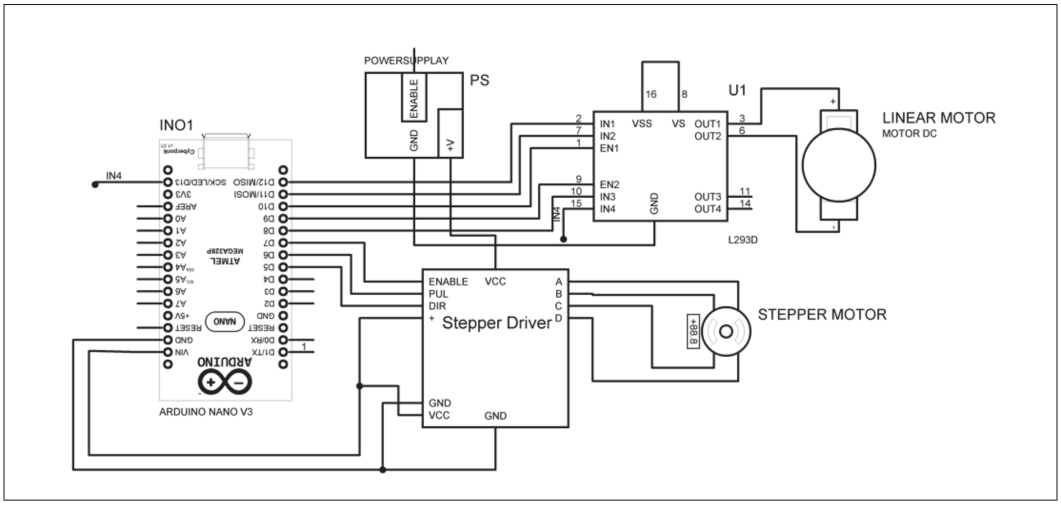

Figure 3.7 Rotational platform schematic diagram

2. **Bluetooth Module**

   Since all the communications are done wirelessly, a separate Bluetooth module is used for the rotational platform prototype. The HC-06 Bluetooth SPP module is used for establishing a transparent wireless serial connection. This module is Bluetooth V2.0 certified and has a data rate of 3 Mbps (Figure 3.8). The commands are sent to the Arduino board using the Bluetooth module to control the motors.

3. **Stepper Motor and Stepper Driver**

   In the prototype, a stepper motor is used to rotate the platform on the vertical axis. This stepper motor is connected to a driver and finally to the Arduino board. The prototype (i.e., mannequin head equipped with a hardhat) can be easily rotated between 0 and 359 degrees using this stepper motor. It is equipped with a 100-to-1 gear ratio gearbox. Therefore, the platform can be easily rotated in steps less than one degree. Additionally, the gearbox helps the platform move more smoothly and handles more pressure while exposed to the high wind speed inside the wind tunnel.

4. **Linear Motor and Bidirectional Driver**

   For prototype, a high torque motor was required to be able to rotate the platform on the

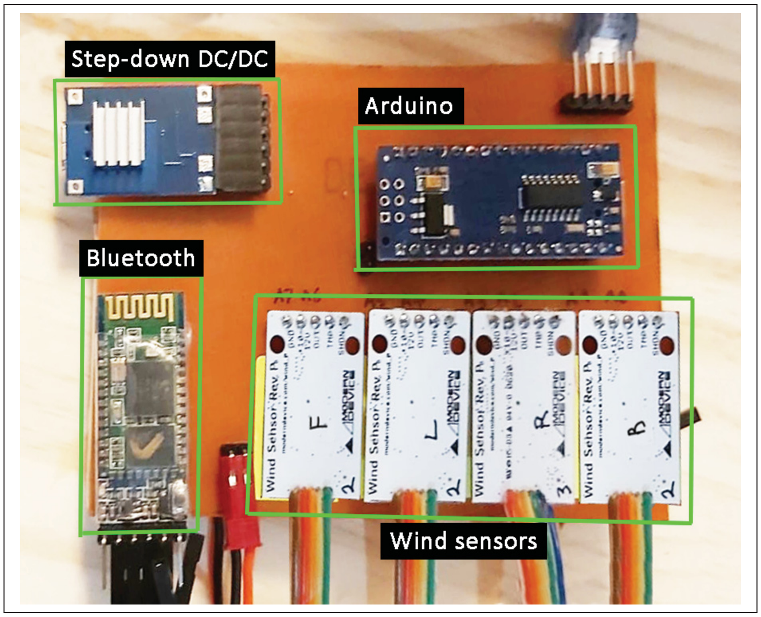

Figure 3.8 Bluetooth module and other components

transverse axis because the equipment attached to this axis was heavy (i.e., the prototyped hardhat, mannequin head, and 3D-printed parts). The linear motor has the highest torque compared to other types. The speed of this type of motor is not high compared to the stepper motor, but its torque is much higher. Therefore, using this type of motor, the platform and the devices attached to it can be easily rotated on the transverse axis. The input voltage of this linear motor is 12 V, and its maximum ampere is 5 A. A bidirectional motor driver with a 7 A output is used to power this linear motor.

5. **Power Supply**

   The most important feature of a power supply is to provide a constant voltage and current. As a result, the voltage and current specification of the power supply datasheet must be accurate. A new generation of the power supply (i.e., XT60) is used that does not get hot even when used for long periods of time. The utilized power source has a voltage of 12 V and a current of 6 A. This power supply is used to power a stepper motor, a linear motor, two motor drivers, an Arduino, and a Bluetooth module.

6. **Assembled Prototype - Rotational Platform**

   All of the components were assembled in the prototype. The accuracy and strength of the joints were important as the prototype is exposed to high wind pressure (inside the wind tunnel) in addition to its weight. After assembling all the parts (shown in Figure 3.9), the prototype was placed inside the wind tunnel test area. In order to place the rotational platform and the hardhat inside the wind tunnel, a base plate is designed and 3D-printed.

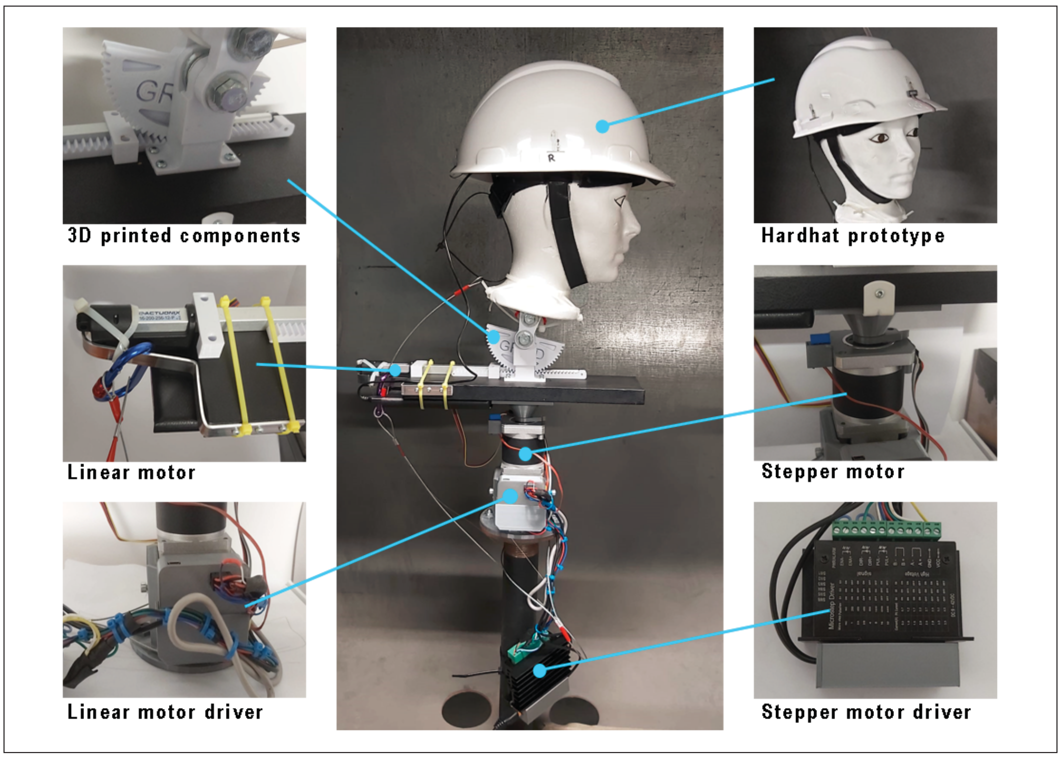

Figure 3.9 Rotational platform components

3.1.2.2 Wind Tunnel

The wind tunnel is the main element of the data collection station. Therefore, the consistency of the airflow generated by the wind tunnel is a critical factor for the data collection. The selected wind tunnel is located at Ecole de Technology Superior (Figure 3.10). This wind tunnel is 10.5 m long and 2.1 m in height. Its cylindrical shape test area has a diameter of 1.3 m and a length of

1.2 m. The opening for the test area is 90 cm*85 cm, hence, the prototype could be easily placed inside the wind tunnel. The wind tunnel can operate in the range of 3.5 to 11.5 m/s. Although the maximum speed of the wind tunnel is 11.5 m/s, we conducted tests with the maximum speed of 10 m/s, as the tunnel started to vibrate at the higher speed rates.

Figure 3.10 Wind tunnel

3.1.2.3 Reference Anemometer

Our reference anemometer was an SP565 thermal anemometer that can measure air velocity and ambient temperature. This anemometer was used to record and share data in real-time. The data resolution of this anemometer was 0.01 m/s, and the measurement range is between 0.2 m/s and 20 m/s. In addition, it could record temperatures between -20 C and 80 C.

3.1.3 Data Collection Station - Implementation

The prototype rotational platform and the hardhat were installed inside the wind tunnel after installing and testing the components and ensuring their performance (Figure 3.11A). In addition to the rotational platform, the data collection station also included reference anemometers (Figure 3.11B) which are installed separately. Figure 3.11C shows the assembled prototype in side the wind tunnel. using this setup, the wind tunnel, reference anemometers, and main power supply for the initial setup and test were verified. Figure 3.11D shows the final installation and configuration of the data collection station.

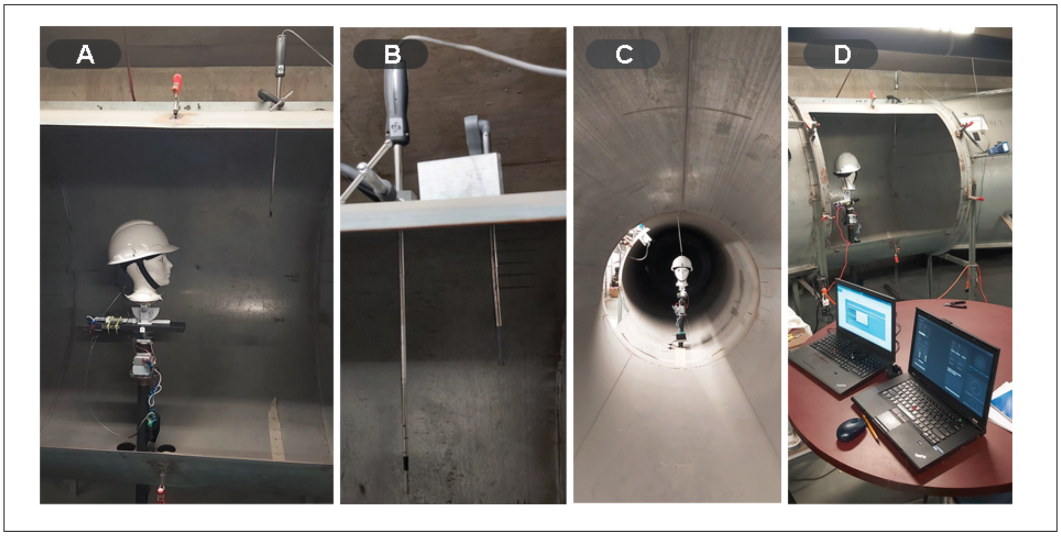

Figure 3.11 Data collection station

Summary

In this section, details about the implementation of the prototype of the proposed system was provided. It included a complete description of the hardhat components and, the description and the implementation of the various parts of the data collection station.

3.2 Dataset Gathering

In order to the predict wind speed and direction based on the input data from hardhat sensors, the use of a supervised machine learning algorithm is proposed. Therefore, to create our models for machine learning, the creation of a dataset is required. The data needs to be carefully organized and stored to implement machine learning models. Furthermore, we must ensure that the measurements are consistent and valid during the data gathering process. Data quality is critical since the data gathered from the data collection station are fed into the machine learning models. The output of the machine learning models can be affected by missing, incomplete, inconsistent, incorrect, or duplicate data. In this research, with the help of the data collection station, accurate data were collected. Figure 3.12 illustrate the general architecture of the data gathering solution. Details about the implementation of the data collection station is elaborated in Section 3.1.2.

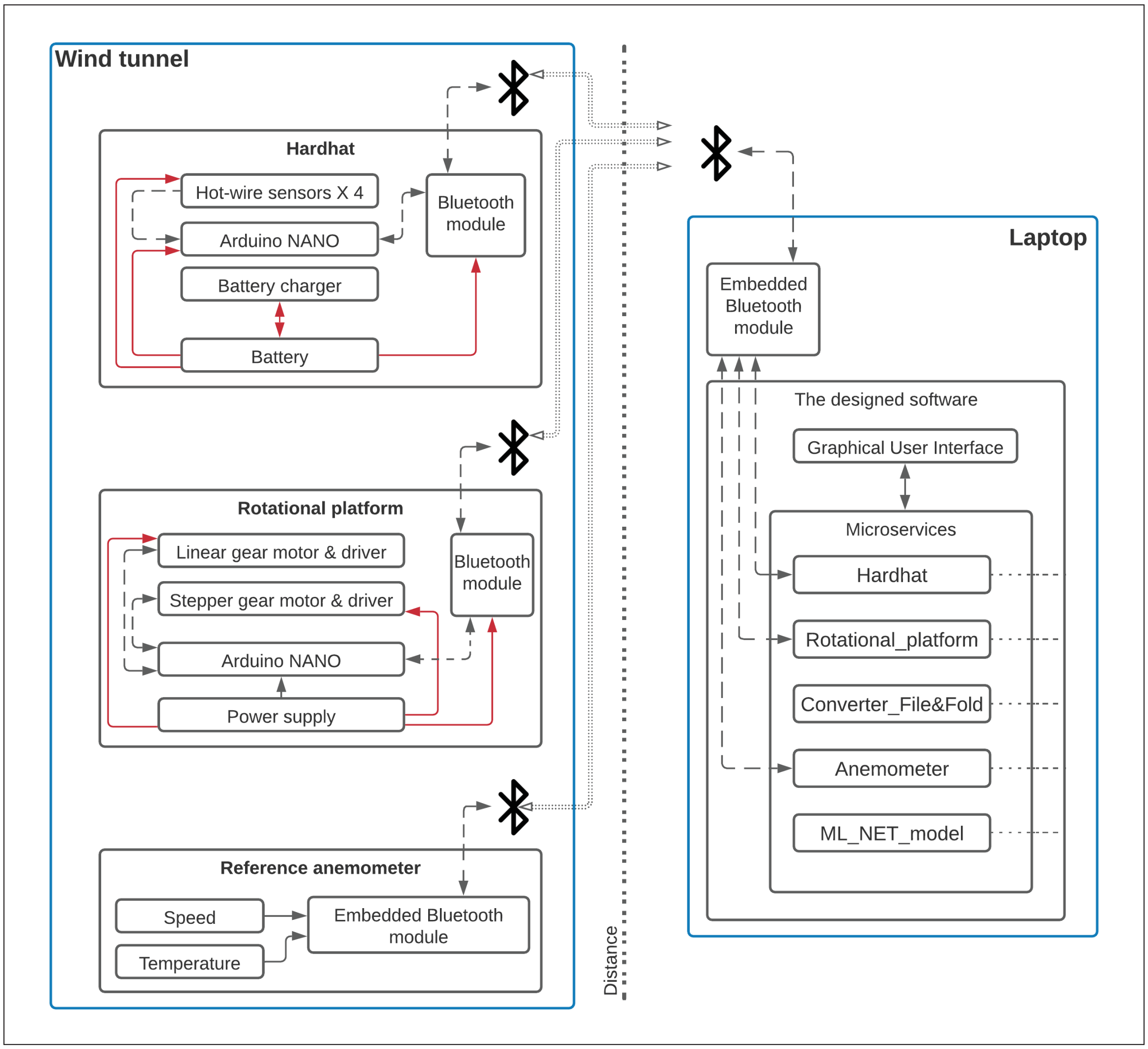

Figure 3.12 General architecture of the data gathering solution

3.2.1 Data Collection Setup

As explained in Section 2.2.2.2, the data collection station consists of the following hardware items: hardhat, wind tunnel, rotational platform, and a reference anemometer. A software application is designed and implemented to control the rotational platform and collect the data from the hardware in real-time. Using this station, required data variables were recorded including, current wind speed, the temperature of the wind tunnel test area, wind exposure direction (the position of transverse and vertical axis from the rotational platform), and readings of hardhat sensors (the data from hot-wire sensors).

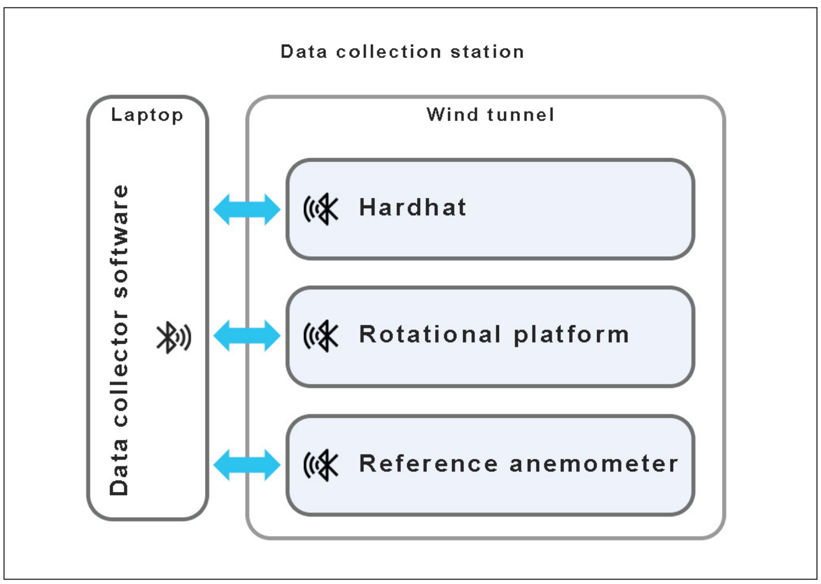

Figure 3.13 Data collection architecture

Bluetooth modules are used to wirelessly transmit data between multiple components of the data collection station. Since the Bluetooth connection is a 1:n (one-to-many relationship), we can connect several Bluetooth devices to one Bluetooth master device for data exchange. In our implemented system, the data collection software can connect to all other three Bluetooth devices (reference anemometer, hardhat sensors, and rotational platform) simultaneously to transmit and receive data.

The developed data collector software controls the exchange of data related to multiple services using wireless communication (Figure 3.13). The data contains service input and output (Section 3.2.1.1 and Section 3.2.1.2) as well as data related to managing and accessing service status. In Figure 3.14 various input and output data to the developed software is listed.

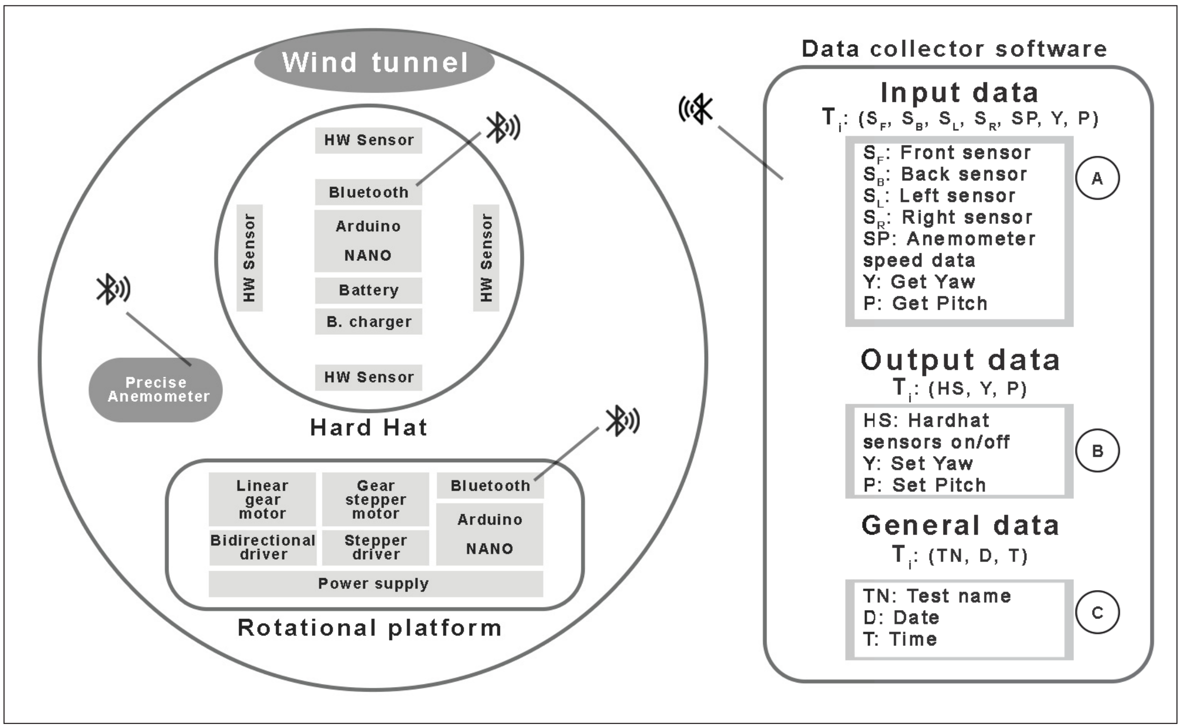

Figure 3.14 Software input/output data

3.2.1.1 Service - Input Data

The input data (Figure 3.14, label A) refers to the data provided to the system core, with a specific interval, or only once after when a particular command is called. This data is provided from three different sources during the data collecting step: from the hardhat (i.e., the data related to four hot-wire sensors), from the rotational platform (i.e.,the data related to the transverse and vertical axis positions, and the wind speed sent from the reference anemometer. These data provide a base to make the dataset.

3.2.1.2 Service - Output Data

The output data (Figure 3.14, label B) is used to control our hardware elements via sending a command. Therefore, using these output data, the hardhat sensors can be turned on and off, and the rotational platform position can be changed on the transverse and vertical axis.

3.2.1.3 General Data

General data (Figure 3.14, label C) are the required information used by the software to add the context to the collected data. These data include the username, the test date and time, related to each sample, etc.

3.2.2 Data Collection Strategy and Procedure

The main strategy of data collection is to measure and record data of hot-wires sensors (as independent variables) when manipulating dependent variables, which are wind speed and wind direction. The goal is to create a dataset of various wind speeds and wind directions with their associated measured values of hot-wire sensors. Hence, when a collection of four readings from hot-wire sensors are given, the wind speed and direction can be predicted using two separate ML models. To build the dataset, for each value of wind speed generated by the wind tunnel, the ambient temperature and the measurement from four hot-wire sensors are collected for a range of pitch and yaw rotation, The ambient temperature was not considered as an input in our ML models, as it was not possible to change it during our data collection, which is one of our limitations, explained in Section 3.4.1.

3.2.2.1 Automated Data Collection

An automated data collection system is designed and implemented. In the developed software, variables are specified by the user. The system can automatically collect data based on these defined variables. The start angle, finish angle, and step size related to the rotation based on the

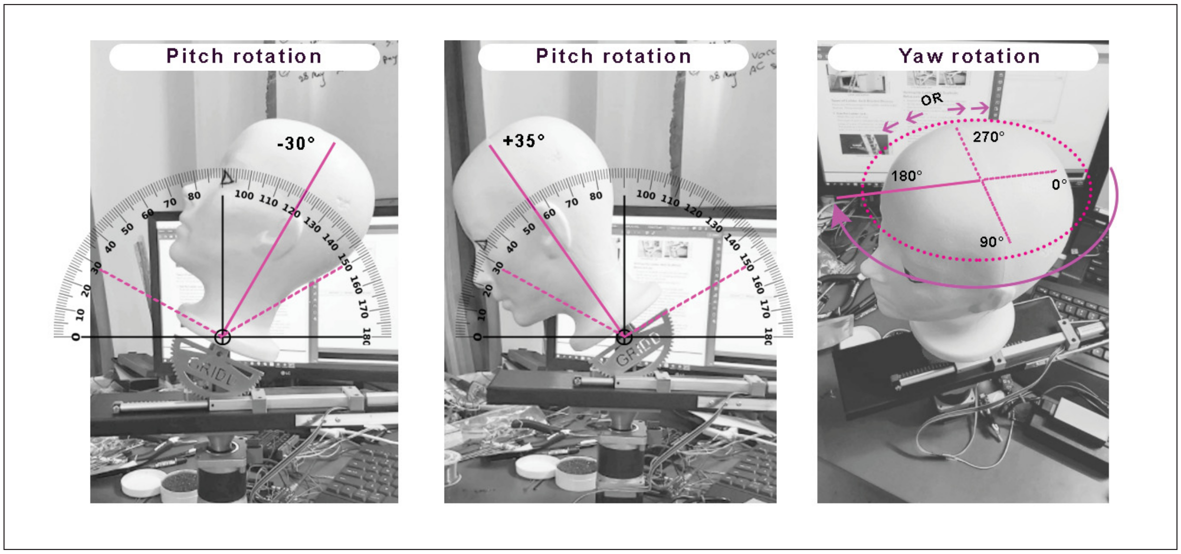

Figure 3.15 Rotation angles around the vertical and transverse axis

transverse and vertical axis, the number of samples per stop, and finally, the delay time to start sampling after each movement, are the variables related to automated data collection. Figure 3.16 shows the automated data collection flowchart and the range of variables.

To run each round of test regarding our data collection, first, we ensured that the ambient temperature was constant. Next, we fixed the wind speed of the wind tunnel, then started to rotate the rotational platform, and for each rotation step, we collected the related data and changed the position for the next data collection stop.

The hardhat can be rotated by 360 degrees around the vertical axis and 120 degrees around the transverse axis using the rotational platform. As a result, we can orient the hardhat in almost all possible positions to gather sample data from four hot-wire sensors. A sample of our dataset is presented in Appendix I, Table-A I-1. The control software allows collecting required data automatically. The data will be saved in comma-separated values (CSV) format to be used for the training process of the machine learning models.

Table 3.1 shows data collection parameters used to generate the initial dataset. Each row of this table defines a separate data collection round called test. Therefore, we defined a specific

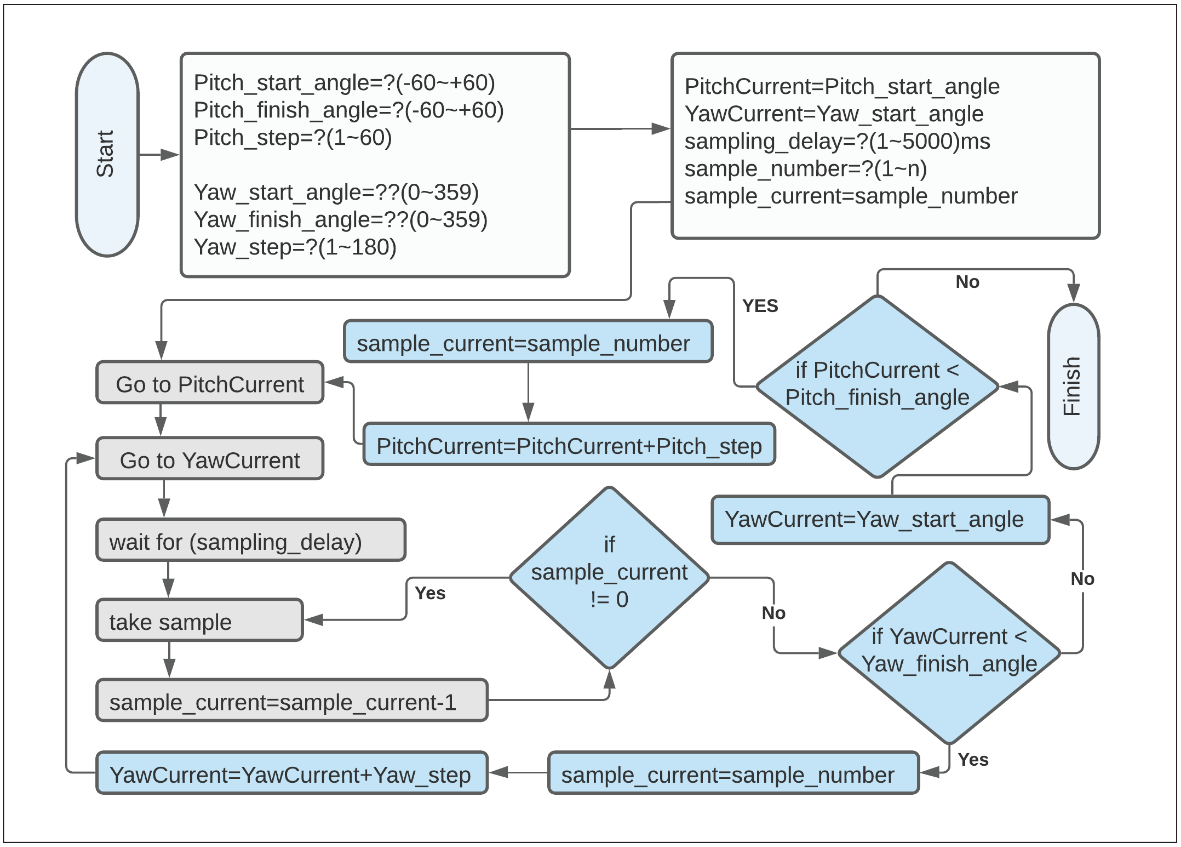

Figure 3.16 Data gathering flowchart

wind speed for the wind tunnel, a specific start and end angle for the transverse and vertical axis related to the rotational platform, the angular change for the next stop, the number of samples per stop, and the amount of latency before starting the data collection after each movement.

Table 3.1 Parameters of each data collection round (test)

Test	Wind Speed (m/s)	Transverse Axis			Vertical Axis			Sample	Delay (ms)
		From	To	Step	From	To	Step		
1	3.5	-40°	+50°	10°	0°	359°	10°	15	1000
2	4.5	-40°	+50°	10°	0°	359°	10°	15	1000
3	5.5	-40°	+50°	10°	0°	359°	10°	15	1000
4	6.5	-40°	+50°	10°	0°	359°	10°	15	1000
5	7.5	-40°	+50°	10°	0°	359°	10°	15	1000
6	8.5	-40°	+50°	10°	0°	359°	10°	15	1000
7	9.5	-40°	+50°	10°	0°	359°	10°	15	1000

3.2.3 Collected Dataset Information and Dimension

The purpose of employing the machine learning model in this study is to predict the wind speed and direction using the provided training data. In this study, we have two separate target variables to predict. The first target variable is the wind speed, and the second one is the wind direction. Our dataset consists of six columns. Four of them are independent variables, and two of them are predictors. Regarding the machine learning models, two separate models were created for the wind speed and direction prediction based on the dataset (Figure 3.17). Moreover, the figure shows the relationship between the independent variables and predictors. Appendix I, Table-A I-1 also shows the sample of the dataset.

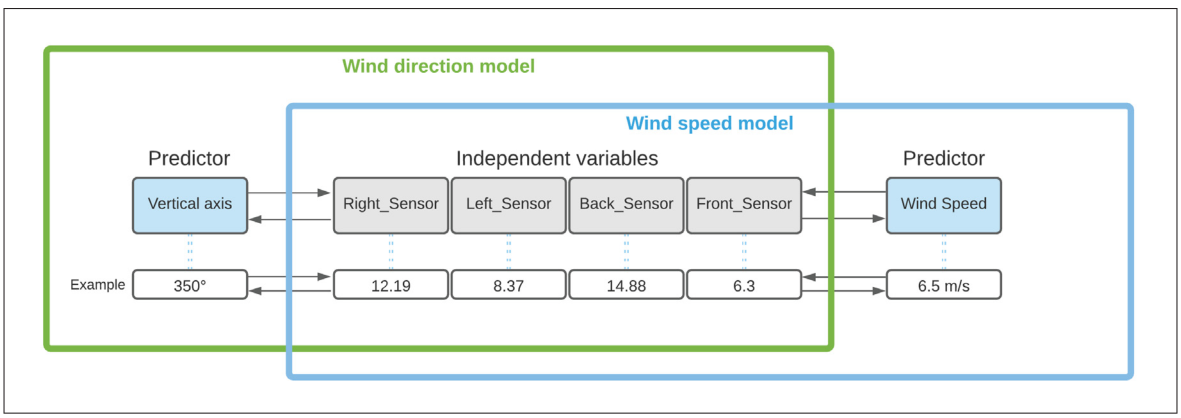

Figure 3.17 Independent variables and predictors

Moreover, to build a machine learning model and evaluate it, one of the important factors is the number of rows related to the dataset. As a result, the algorithms for predicting and evaluating machine learning models differ depending on the volume of data. Our dataset contains 37,000 samples which shows to be adequate for the training and validation of the models. The number of collected samples can be calculated to using values presented in Table 3.1 as follows:

$$TotalSamples = TransverseAxisStops \times VerticalAxisStops \times Tests \times Samples$$

The data transmitted by the hardhat are saved to a separate CSV file after a complete rotation around the vertical axis, consequently for each 360-degree rotation on the vertical axis, a separate file will be generated. Appendix I, Table-A I-1 also shows the sample of our dataset. Furthermore, the data are controlled in real-time. In some cases, the data related to one or more sensors are failed to be added, and as a result, the entire data from the four sensors in that time frame must be ignored.

Finally, we combined the files using "FormatConverter" and "Combiner" methods, described in Section 2.2.3.1, and prepare the files to build two different machine learning models related to wind speed and direction prediction.

Summary

This section described the data collection setup, strategy, and procedure, as well as the dataset and its dimensions required to create our machine learning models.

3.3 Training and Validation

To build the machine learning models, collect metrics, and measure the performance of the models, the ML.NET is used. In Section 3.3.1, the machine learning algorithm used in this study is discussed. The validation scenario and method are elaborated in Section 3.3.2. Finally, in Section 3.3.3 the evaluation methods to measure various metrics for the trained models are proposed.

3.3.1 Model Training

In this study, two separate models were developed to predicts the wind speed and the direction, as two dependent variables (predictors)(elaborated in Section 3.2.3). The machine learning models are trained using LightGBM (Light Gradient Boosting Machines) algorithm that explores the relationship between one or more independent variables (i.e., the data from hardhats sensors) to be able to measure one variable called dependent or predictor (i.e., wind speed or direction) (Hawkins, 2004). LightGBM is a highly efficient gradient boosting decision tree. In several machine learning tasks, Gradient Boosted Decision Trees (GBDT) provides state-of-the-art performance, and due to its efficiency, accuracy, and interpretability, it is a frequently used machine learning technique. The GBDT is a sequence-trained ensemble model of decision trees. LightGBM accelerates the training process by up to 20 times compared to Gradient Boosting Machines while maintaining almost the same accuracy as traditional GBDT (Ke *et al.*, 2017).

3.3.1.1 Overfitting Issue

All sciences that use quantitative measurements rely on model fitting (Hawkins, 2004). If the model does not generalize well from the training dataset to the test data, this problem is called overfitting (Hawkins, 2004; Yadav & Shukla, 2016). Training should be conducted in such a way that although the model has enough examples to train on, they do not over-fit the model. Additionally, if there are not enough instances to train on, the model will not be adequately trained and will produce poor results when tested (Yadav & Shukla, 2016). Cross-validation is the most common method for overfitting. The cross-validation method used in this study is explained in Section 3.3.2.

3.3.2 Validation Scenario

Identifying the model validation method is essential in developing any ML model. To evaluate a model, it is possible to train it on the entire dataset and then evaluate it by testing how well it performs on that same data. This results in an evaluation metric known as "training accuracy". In this process, even if the predicted outcomes show 99% accuracy, the model can not still be judged as a perfect model as it must be checked with the “unseen” data (Hawkins, 2004; Yadav & Shukla, 2016). A major issue with machine learning is that it is impossible to know how well a model performs on new data until the model is tested. Cross-validation is the most frequent method for evaluating a model’s performance (Yadav & Shukla, 2016). In this study, K-fold cross-validation is used to validate our ML models.

When working with small datasets, the best option is k-fold cross-validation with a big value of k, but this value must be less than the number of instances (Yadav & Shukla, 2016). Having a large number of estimates is preferable to obtain reliable performance estimation or for comparison. The number of estimates obtained in k-fold cross-validation equals k. In general, the larger value of k provides better cross-validation accuracy (Yadav & Shukla, 2016). The benefit of k-fold cross-validation is that all of the instances in the dataset are finally used for both training and testing.

Since our data are recorded sequentially in the data collection step (explained in Section 3.2), the data on the initial dataset rows are sorted based on wind speed. Hence, before running the k-fold cross-validation process, the data must be reshuffled and re-stratified. During the data collection process, more than 37,000 samples was collected, which created a colossal dataset, and is adequate to train and evaluate the models.

For k-fold cross-validation method, the data is partitioned into five subsets (K=5), called folds. Then, the algorithm was iteratively trained on k-1 folds while using the remaining fold (called the "holdout fold") as the test set (Figure 3.18).

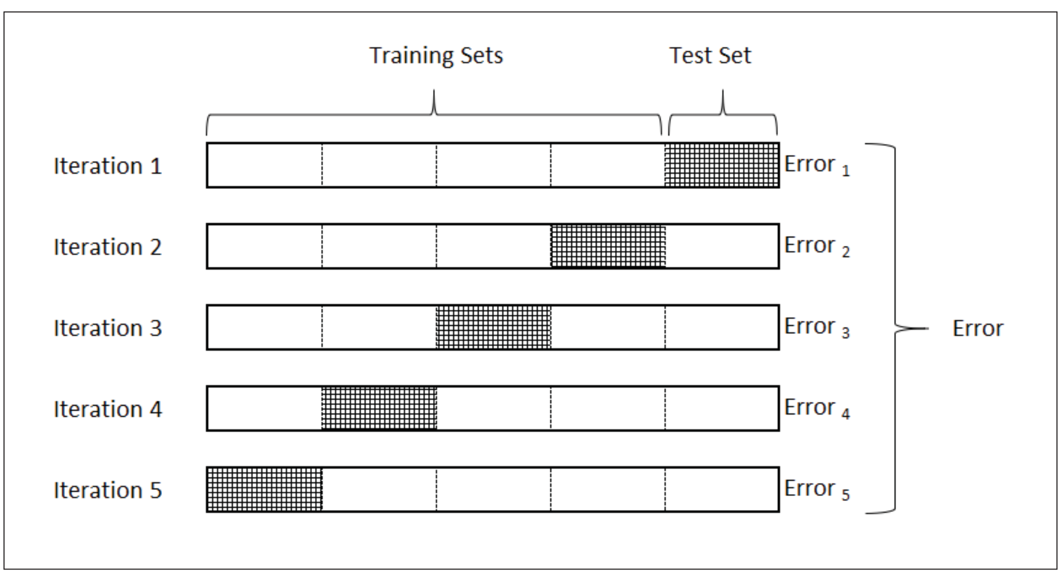

Figure 3.18 Fold partitions and iterations

Multiple training and test datasets based on the number of folds need to be created. The total number of training and test datasets will be k*2 ,and the number of iterations will be equal to k. A software application is developed to automate the process. It makes the folding process easier, faster, and more accurate (Figure 3.19).

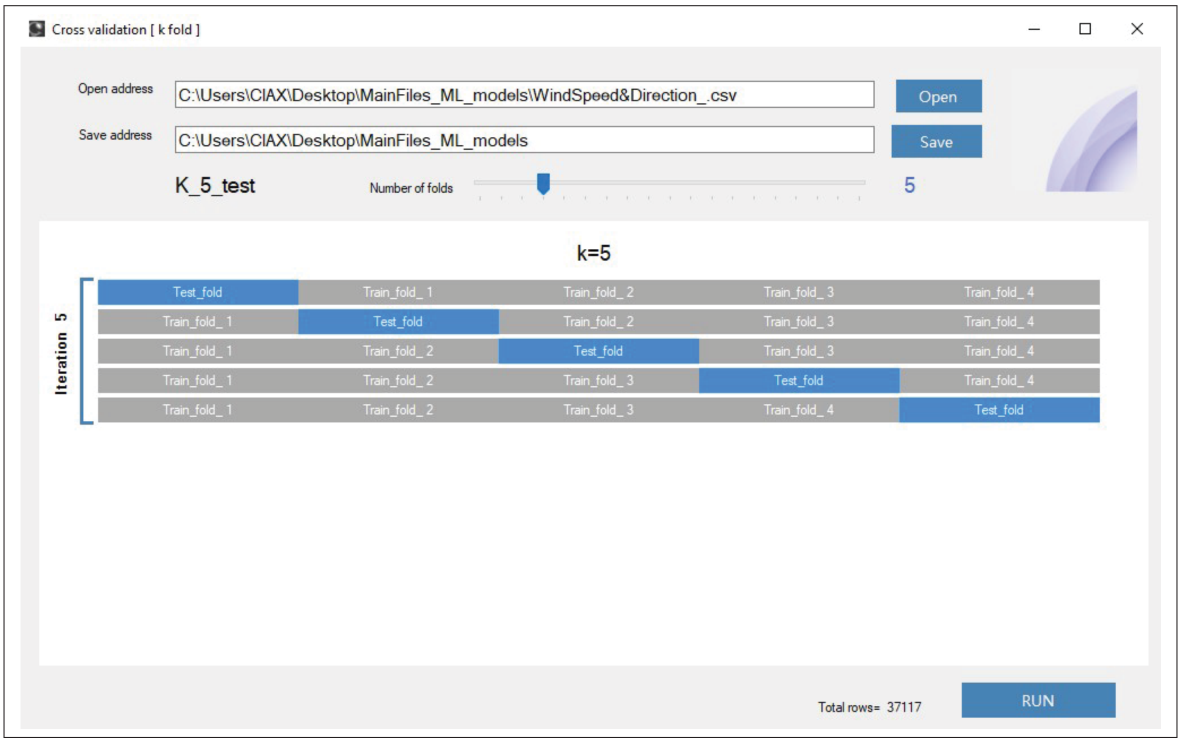

Figure 3.19 Fold divider software GUI

First, the model is trained on 80% of our dataset, and as a result, the number of rows for the trained model became approximately 29,600. The second part is the test samples which is 20% of our dataset. The number of test rows becomes approximately 7,400 samples.

In the k-fold cross-validation process, five separate learning experiments were conducted for each model (wind speed and wind direction), explained in Section 3.3.1. In each iteration, one of the five sets was selected for test data, and the remaining four sets were combined as the training set. The models are tested using the LightGBM algorithm, and the average error rate of five test cases is used to calculate the true error.

3.3.3 Validation Analysis and Results

ML.NET provides evaluation methods to measure various metrics for the trained model.

3.3.3.1 Evaluation Metrics

Regarding the regression model, there are four different evaluation metrics (Na, 2019):

1. R-squared or Coefficient of determination.
2. Mean absolute error (MAE).
3. Mean Squared Error (MSE).
4. Root Mean Squared Error (RMSE) or Root Mean Square Deviation (RMSD).

A commonly used metric in the evaluation of regression model is the R-squared. The values of the wind speed or wind direction of the test dataset are compared with the output predictions to calculate the metrics.

To calculate the mean of each metric for wind speed and direction independently, we calculated the metric values separately for each of the ten available models (explained in Section 3.3.2). Table 3.2 and Table 3.3 show the metrics used to evaluate our initial models (wind speed and direction prediction models).

3.3.3.2 Evaluation Results

Our evaluation results show that the wind speed models are more accurate than wind direction models. The mean R-squared related to wind speed is 0.91, whereas it is 0.83 for the wind direction. All of the models produce similar results for relevant metrics measures.

Table 3.2 Wind speed model evaluations

#	Train & Test					Metrics			
						R-squared	**Absolute loss**	**Squared loss**	**RMS loss**
1	Test					0.906	0.362	0.241	0.491
2		Test				0.903	0.361	0.246	0.496
3			Test			0.908	0.359	0.236	0.486
4				Test		0.906	0.362	0.236	0.486
5					Test	0.911	0.358	0.228	0.478
Mean						**0.9068**	**0.3604**	**0.2374**	**0.4874**

Table 3.3 Wind direction model evaluations

#	Train & Test					Metrics			
						R-squared	**Absolute loss**	**Squared loss**	**RMS loss**
1	Test					0.827	21.954	1880.837	43.369
2		Test				0.824	22.24	1894.655	43.528
3			Test			0.828	22.489	1863.789	43.172
4				Test		0.837	21.674	1761.398	41.969
5					Test	0.836	21.641	1759.333	41.944
Mean						**0.8304**	**21.9996**	**1832.0024**	**42.7964**

Summary

In this Section, we provided details about the use of a supervised machine learning algorithm. We described the LightGBM algorithm that was used to train the machine learning models as well as the method for evaluating the performance of our models and evaluation metrics.

3.4 Discussion

In Section 3.4.1, the limitation of the implemented prototype is discussed. The challenges faced in the project, including the design and implementation of the prototype is elaborated in Section 3.4.2. Finally, in Section 3.4.3 some improvement scenarios are proposed.

3.4.1 Limitations

The main limitation in the creation of the dataset was the lack of control over the ambient temperature for the data collection station. Although the ambient temperature remained constant during our data collection, we could not change the temperature to collect new data. Hence, the dataset only includes the results of data collection when the ambient temperature of the environment is between 24 and 25 degrees Celsius.

One of the limitations of the data collection station was the operating range of wind speed produced by the wind tunnel, which consequently had an effect on the dataset. The prototype hardhat could be only tested in the wind speed range between 3.5 m/s to 10.5 m/s. This limitation affects the accuracy of the machine learning models when the actual wind exceeds this range, as our machine learning models is trained on the data collected from this range. Therefore, the accuracy will be increased for high wind speed if the data related to higher speed (higher than 10.5m/s) is added to the models.

Regarding the limitations of the prototype hardhat, our prototype can communicate wirelessly within the range of 60 m. The range can be extended if the prototype sends and receives data over the internet using other communication modules, such as Long-Term Evolution (LTE). Moreover, the capacity of the battery used for the prototype allows only 20 minutes of operation. To avoid this problem during the data gathering phase, the prototype was directly connected into the power source using a USB cable.

Another limitation is related to the quality of 3D-printed parts of the rotational platform. As the type of printed materials was Polyethylene Terephthalate Glycol (PETG), there were limitations regarding the physical strength of the parts which limits its use within a certain amount of wind force applied to the rotational platform. Although the platform could resist the maximum wind speed when there was no rotation, it was probable that the 3D-printed components of the platform would shatter if the platform was horizontally or vertically rotated.

The proposed system has to be tested and validated in the construction site. this study showed the results of the performance of the system using data generated by the wind tunnel and in a controlled environment. Further field testing is required to validate the method.

3.4.2 Challenges of The Prototype Implementation

We faced many challenges when designing and implementing mechanical parts of the rotational platform, which rotates simultaneously in two axes. Additionally, various challenges were faced in the design and implementation of the prototype hardhat components such as Bluetooth module, DC- to-DC converter, and an Arduino board. To overcome the challenges of connecting all elements in a limited space, a Printed Circuit Board (PCB) is designed and created.

Regarding the life-size mannequin head, its material needed to be carefully chosen as the rotational platform could handle a limited range of weight. So it was essential to find a lightweight mannequin to move easily by the motors. Furthermore, the mannequin was to be exposed to a high wind force. Consequently, finding a mannequin with the right material properties which does not break during tests was challenging.

During the experimentation phase, several units, such as the prototype hardhat, the rotational platform, and the reference anemometer, were sending a high rate of data to the processing software. Hence, synchronization of all real-time data gathered from four hot-wire sensors, the rotational platform, the reference anemometer, and ensure their quality was a challenging task.

3.4.3 Improvement Scenarios for The Prototype

The prototype software system can be improved by adding an alert functionality. The alert system would communicate dangerous conditions to workers, security managers, and machine operators based on a set guideline. If the detected wind speed value exceeded the reference values, the alert system can notify related contact.

Another improvement is related to the rotational platform. The quality of the platform material can be improved. For example, instead of 3D-printing with PETG, elements made of aluminium can be used.

The accuracy of the prediction module will improve if the dataset is fed with more data related to higher wind speed as well as various ambient temperatures.

CONCLUSION AND RECOMMENDATIONS

Summary

This research proposed an innovative solution to identify wind speed and direction in real-time, via using supervised machine learning algorithm and hot-wire sensors attached to hardhats of construction workers. This study was conducted in three phases to develop the solution: a comprehensive literature review, developing framework and the prototype, and verification and testing. First, a comprehensive literature review was conducted to understand the previous research limitations and findings. In the second phase, an innovative solution together with a prototype was developed, and related data were collected using a data collection station. In the third phase of this study, the collected data from the second phase were analysed to determine the functionality, accuracy, and reliability of the proposed solution.

The main component of the proposed solution was a hardhat equipped with four hot-wire sensors. Various experiments were performed to collect the data from the prototype hardhat sensors. Finally, we used the data collection station to create the dataset to be fed into the machine learning models.

This study faced several challenges, including challenges related the development of the prototype, simulation of wind's direction, and the validation of the collected data. These challenges were addressed using innovative approaches, as elaborated in the previous Sections. The results showed that the solution can predict the wind's speed and direction in real-time using the developed machine learning models.

Conclusions

In this research, a study was conducted on real-time monitoring and predicting of wind speed and direction. The proposed solution responds to the research questions of this study introduced in Chapter 1. The solution corresponds to the limitation of traditional methods that are using the weather data from a website or a local weather station (placed in the construction site), which cannot measure the wind parameters in specific locations and in real-time. The proposed solution integrated hot-wire sensors into the hardhat to respond to the problems related to the impact of wind on the safety of construction sites. The research contributes to the scientific body knowledge by proposing a new method to address the discussed safety issues in construction sites.

Moreover, the results of this research can be used to improve the safety of construction sites by reducing the risk of incidents and accidents via providing automatic alerts to workers and security managers in a real-time. Furthermore, implementing hardhats equipped with IoT sensor for construction safety provides opportunities for various future research projects related to safety. The machine learning algorithm is used in this study to predict the wind speed and direction. The results suggest that the wind's speed and direction can be accurately predicted in real-time using the proposed solution.

Perspectives for Future Research

The most important future work will be the validation of the method on a construction site. By testing the developed system in the construction site, possible new challenges and improvement scenarios can be identified.

In our hardhat setup, the hardware prototype sends and receives data to the local processing software on a PC via Bluetooth communication. The solution can be extended to support cloud communication for data transmission. The prototype can be connected to the internet using communication methods, such as WiFi, through minor adjustments.

The dataset needs to be expanded by including more data related to various ambient temperatures. For that, having a large wind tunnel placed in a temperature-controlled environment is required.

Moreover, the developed software can be further extended to include safety alerts. Consequently, the software will be able to deliver immediate feedbacks and alerts to the security agent for further actions. More specifically, the software can compare wind speed and direction with the reference values presented in safety regulations, and when the wind speed passes the specific thresholds, it automatically sends an alert to the worker or security agent (for example, to guide workers to wear their safety glasses or to stop working at height).

APPENDIX I

DATA GATHERING

Table-A I-1 The dataset was gathered using the wind tunnel installation and the rotating platform

Vertical axis	Right sensor	Left sensor	Back sensor	Front sensor	Wind speed
180	8.36	1.32	8.5	1.01	4.5
180	8.91	1.42	8.62	1.05	4.5
180	8.91	1.22	8.37	0.94	4.5
180	8.91	1.68	8.29	0.9	4.5
180	9.09	1.37	8.37	1.11	4.5
290	4.51	20.48	2.48	10.87	6.5
290	4.74	19.83	2.32	11.08	6.5
290	4.07	20.14	2.86	11.3	6.5
290	4.18	19.51	2.39	10.65	6.5
290	4.18	20.45	2.86	11.05	6.5
280	3.87	23.23	4.86	14.05	7.5
280	3.87	23.87	4.4	14.11	7.5
280	4.07	23.73	4.29	14.09	7.5
280	4.18	24.32	4.51	14.11	7.5
280	4.18	23.92	4.5	14.15	7.5
130	4.74	11.3	13.36	21.48	8.5
130	4.29	11.51	13.36	21.82	8.5
130	4.07	11.12	13.32	21.11	8.5
130	3.97	11.87	12.41	21.48	8.5
130	4.62	11.96	13.86	21.14	8.5

Table-A I-2 Wind tunnel specification

Small Wind Tunnel (Open Return)	
Minimum speed	0.2 m/s
Maximum speed	5.0 m/s
Test section size	60 mm diameter

APPENDIX II

HOT-WIRE SENSOR TESTS

Figure-A II-1 The small wind tunnel

Figure-A II-2 Hot-wire reference anemometer

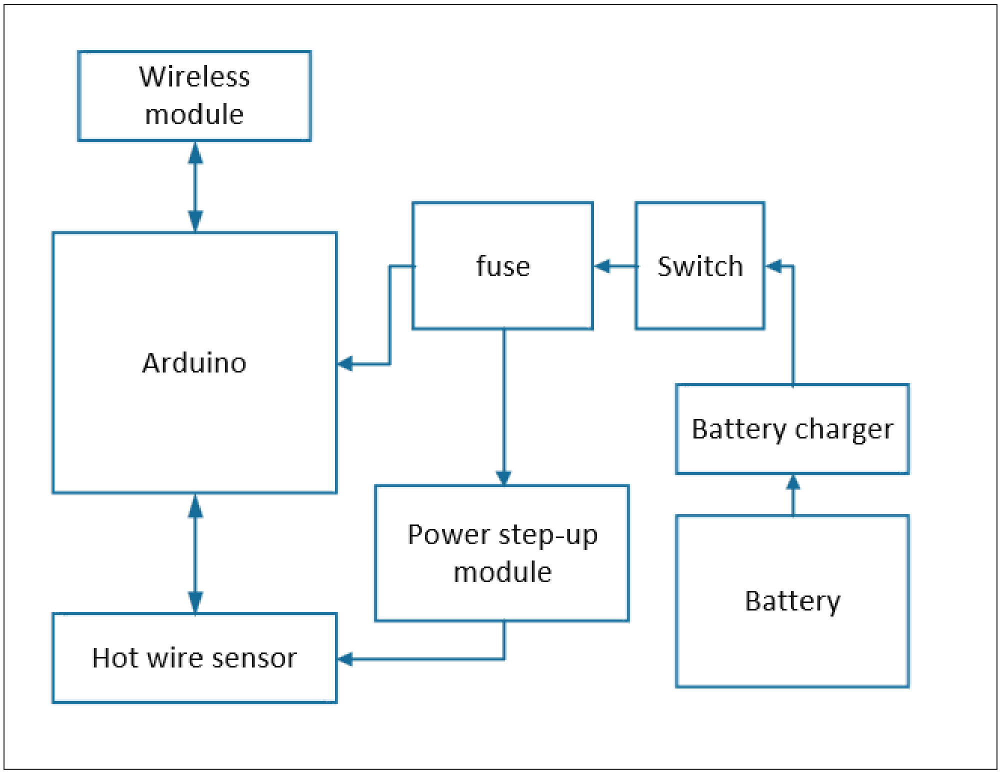

Figure-A II-3 The block diagram of the hot-wire sensor test circuit

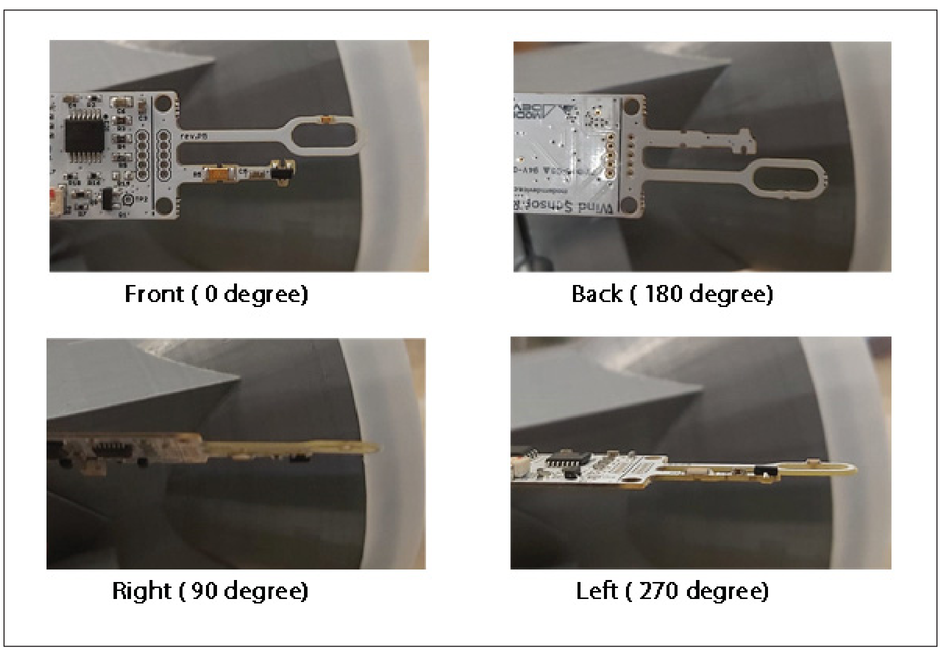

Figure-A II-4 Four different angles of Hot-wire sensor inside the small wind tunnel

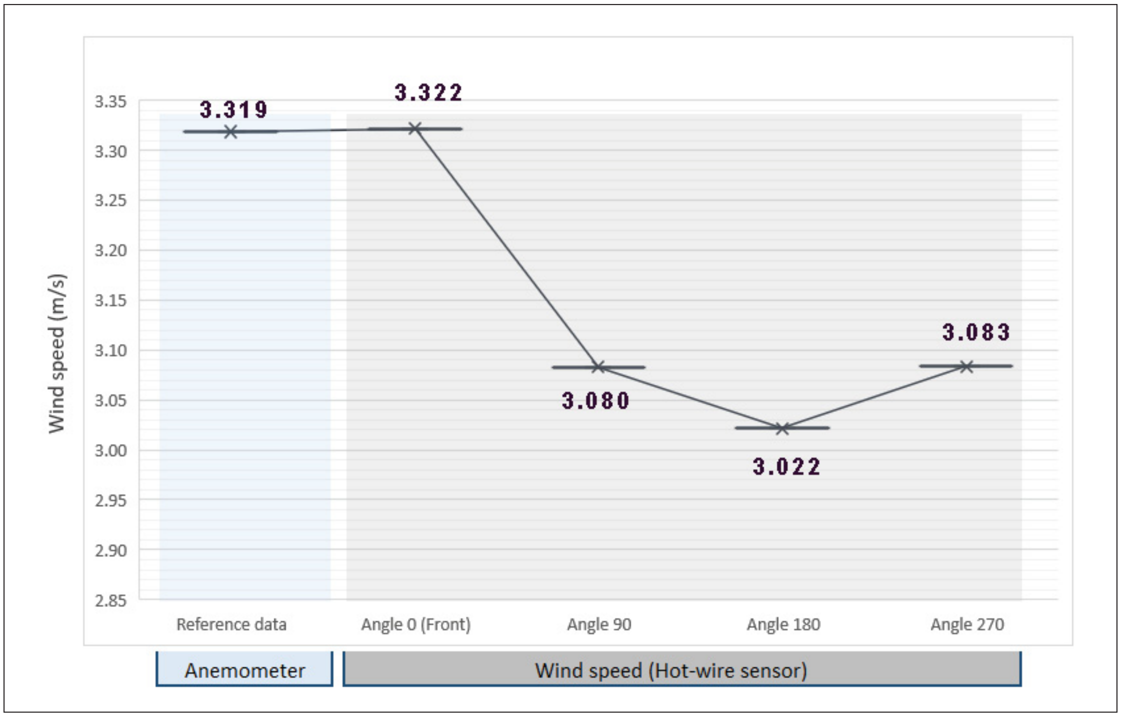

Figure-A II-5 The offset between wind speed data (the data from reference anemometer and Hot-wire sensor exposed to wind from different angles)

BIBLIOGRAPHY

Abderrahim, M., Garcia, E., Diez, R. & Balaguer, C. (2005). A mechatronics security system for the construction site. *Automation in construction*, 14(4), 460–466.

Acharya, P., Boggess, B. & Zhang, K. (2018). Assessing heat stress and health among construction workers in a changing climate: a review. *International journal of environmental research and public health*, 15(2), 247.

Adjiski, V., Despodov, Z., Mirakovski, D. & Serafimovski, D. (2019). System architecture to bring smart personal protective equipment wearables and sensors to transform safety at work in the underground mining industry. *Rudarsko-geološko-naftni Zbornik*, 34(1).

Aliyev, A., Zhou, B., Hevesi, P., Hirsch, M. & Lukowicz, P. (2020). HeadgearX: a connected smart helmet for construction sites. *Adjunct Proceedings of the 2020 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2020 ACM International Symposium on Wearable Computers*, pp. 184–187.

Altamura, A., Inchingolo, F., Mevoli, G. & Boccadoro, P. (2019). SAFE: Smart helmet for advanced factory environment. *Internet Technology Letters*, 2(2), e86.

Alvarez, G., Casinillo, G., Goich, A. & Soares, F. (2017). Smart Hard Hat Applied in the Electric Power Industry. *Global Partnerships for Development and Engineering Education: Proceedings of the 15th LACCEI International Multi-Conference for Engineering, Education and Technology, July 19-21, 2017, Boca Raton, FL, United States*, pp. 532.

Arcayena Jr, R. D., Ballarta, A. D., Claros, K. N. & Pangantihon Jr, R. S. (2019). Development of Arduino Microcontroller-based Safety Monitoring Prototype in the Hard Hat. *Proceedings of the 2019 6th International Conference on Bioinformatics Research and Applications*, pp. 119–124.

Ballesteros-Pérez, P., Smith, S. T., Lloyd-Papworth, J. G. & Cooke, P. (2018). Incorporating the effect of weather in construction scheduling and management with sine wave curves: application in the United Kingdom. *Construction management and economics*, 36(12), 666–682.

Budhathoki, N. K. & Zander, K. K. (2019). Socio-economic impact of and adaptation to extreme heat and cold of farmers in the food bowl of Nepal. *International journal of environmental research and public health*, 16(9), 1578.

Chen, B., Zhu, Y.-Q., Yi, Z., Qin, M. & Huang, Q.-A. (2015). Temperature effects on the wind direction measurement of 2D solid thermal wind sensors. *Sensors*, 15(12), 29871–29881.

Cheng, J.-N., Chang, H.-Y., Fu, M.-Y. & Liu, W.-F. (2019). Fiber anemometer for simultaneously measuring wind speed and wind direction. *Microwave and Optical Technology Letters*, 61(4), 891–896.

Cobo, M. J., López-Herrera, A. G., Herrera-Viedma, E. & Herrera, F. (2011). Science mapping software tools: Review, analysis, and cooperative study among tools. *Journal of the American Society for information Science and Technology*, 62(7), 1382–1402.

Dalton, B., Suncorp, S., Chen, A. S., Cazzaniga, M., Zurich, S. R. W. & Re, S. The effect of adverse weather on construction sites.

Dogbe, K., Glyde, H., Nguyen, T., Papathemistocleous, T., Marquand, K. & Bennett, P. (2020). Smart Hard Hat: Exploring Shape Changing Hearing Protection. *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*, pp. 1–6.

Esmaeili, B. & Hallowell, M. R. (2012). Diffusion of safety innovations in the construction industry. *Journal of Construction Engineering and Management*, 138(8), 955–963.

Fyffe, D., Langenderfer, C. & Johns, C. (2016). The Smart Hard Hat.(2016). *Honors Research Projects*, 267.

Gaikwad, P. V. & Kalshetty, Y. R. (2017). Bluetooth based smart automation system using Android. *International Journal of New Innovations in Engineering and Technology*, 7(3), 24–29.

Ghani, N., Tariq, F., Javed, H., Nisar, N. & Tahir, A. (2020). Low-temperature health hazards among workers of cold storage facilities in Lahore, Pakistan. *Medycyna pracy*, 71(1), 1–7.

Gholitabar, S. & Griffis, F. (2019). Correlations Between Wind Speeds and Construction Incidents. *International Conference on Smart Infrastructure and Construction 2019 (ICSIC) Driving data-informed decision-making*, pp. 261–265.

Gubbi, J., Buyya, R., Marusic, S. & Palaniswami, M. (2013). Internet of Things (IoT): A vision, architectural elements, and future directions. *Future generation computer systems*, 29(7), 1645–1660.

Hawkins, D. M. (2004). The problem of overfitting. *Journal of chemical information and computer sciences*, 44(1), 1–12.

Hellerstein, J. M., Hong, W. & Madden, S. R. (2003). The sensor spectrum: technology, trends, and requirements. *ACM SIGMOD Record*, 32(4), 22–27.

Hevner, A. & Chatterjee, S. (2010). Design science research in information systems. In *Design research in information systems* (pp. 9–22). Springer.

Huang, F.-L., Liao, Z.-Z., Wang, T.-H., Chen, Q.-M., Wu, T.-H. & Chang, C.-H. (2019). Intelligent and Disaster Prevention Hard Hat Based on AIOT and Speeches Recognition. *2019 International Conference on Machine Learning and Cybernetics (ICMLC)*, pp. 1–5.

Huang, X. & Hinze, J. (2003). Analysis of construction worker fall accidents. *Journal of construction engineering and management*, 129(3), 262–271.

Johannesson, P. & Perjons, E. (2014). A method framework for design science research. In *An Introduction to Design Science* (pp. 75–89). Springer.

Jung, M., Park, M., Lee, H.-S. & Kim, H. (2016). Weather-delay simulation model based on vertical weather profile for high-rise building construction. *Journal of construction engineering and management*, 142(6), 04016007.

Kamiński, Z. & Czyż, Z. (2017). The characteristics of the operating parameters of the vertical axis wind turbine for the selected wind speed. *Advances in Science and Technology. Research Journal*, 11(1).

Kanan, R., Elhassan, O. & Bensalem, R. (2018). An IoT-based autonomous system for workers' safety in construction sites with real-time alarming, monitoring, and positioning strategies. *Automation in Construction*, 88, 73–86.

Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q. & Liu, T.-Y. (2017). Lightgbm: A highly efficient gradient boosting decision tree. *Advances in neural information processing systems*, 30, 3146–3154.

Keevers, T. L. (2019). Cross-validation is insufficient for model validation. *Joint and Operations Analysis Division, Defence Science and Technology Group: Victoria, Australia*.

Kim, S. H., Wang, C., Min, S. D. & Lee, S. H. (2018). Safety helmet wearing management system for construction workers using three-axis accelerometer sensor. *Applied Sciences*, 8(12), 2400.

Kitchenham, B. (2004). Procedures for performing systematic reviews. *Keele, UK, Keele University*, 33(2004), 1–26.

Kocakulak, M. & Butun, I. (2017). An overview of Wireless Sensor Networks towards internet of things. *2017 IEEE 7th annual computing and communication workshop and conference (CCWC)*, pp. 1–6.

Kosuda, T., Nakajo, Y., Sasagawa, K., Nishikai, Y., Shimizu, S., Kumita, Y., Kondo, T. & Hashimoto, N. (2019). Development of a helmet-type wearable device capable of measuring perspiration during various activities. *2019 International Conference on Electronics Packaging (ICEP)*, pp. 138–143.

Krstajic, D., Buturovic, L. J., Leahy, D. E. & Thomas, S. (2014). Cross-validation pitfalls when selecting and assessing regression and classification models. *Journal of cheminformatics*, 6(1), 1–15.

Larsson, R. & Rudberg, M. (2019). Impact of Weather Conditions on In Situ Concrete Wall Operations Using a Simulation-Based Approach. *Journal of Construction Engineering and Management*, 145(7), 05019009.

Lee, I. & Lee, K. (2015). The Internet of Things (IoT): Applications, investments, and challenges for enterprises. *Business Horizons*, 58(4), 431–440.

Li, C. Z., Zhong, R. Y., Xue, F., Xu, G., Chen, K., Huang, G. G. & Shen, G. Q. (2017). Integrating RFID and BIM technologies for mitigating risks and improving schedule performance of prefabricated house construction. *Journal of cleaner production*, 165, 1048–1062.

Li, G.-Z., Zhao, S. & Zhu, R. (2018). Wearable anemometer with multi-sensing of wind absolute orientation, wind speed, attitude, and heading. *IEEE Sensors Journal*, 19(1), 297–303.

Lu, T.-F. (2013). Indoor odour source localisation using robot: Initial location and surge distance matter? *Robotics and Autonomous Systems*, 61(6), 637–647.

Luis,Genevieve, Y. (2019). Evaluation metrics for Regression and Recommendation [Format]. Retrieved from: https://docs.microsoft.com/en-us/dotnet/machine-learning/resources/metrics.

Makris, P., Skoutas, D. N. & Skianis, C. (2012). A survey on context-aware mobile and wireless networking: On networking and computing environments' integration. *IEEE communications surveys & tutorials*, 15(1), 362–386.

Márquez-Sánchez, S., Campero-Jurado, I., Herrera-Santos, J., Rodríguez, S. & Corchado, J. M. (2021). Intelligent Platform Based on Smart PPE for Safety in Workplaces. *Sensors*, 21(14), 4652.

Mehata, K., Shankar, S., Karthikeyan, N., Nandhinee, K. & Hedwig, P. R. (2019). IoT based safety and health monitoring for construction workers. *2019 1st International Conference on Innovations in Information and Communication Technology (ICIICT)*, pp. 1–7.

Moohialdin, A. S. M., Lamari, F., Miska, M. & Trigunarsyah, B. (2019). Construction worker productivity in hot and humid weather conditions: A review of measurement methods at task, crew and project levels. *Engineering, Construction and Architectural Management*.

Na, L. (2019). ML.NET Metrics - ML.NET. ML.NET metrics - ML.NET [Microsoft Docs]. Retrieved from: https://docs.microsoft.com/en-us/dotnet/machine-learning/resources/metric.

Na, L. (2021). What Is ML.NET And How Does It Work? - ML.NET. What is ML.NET and how does it work? - ML.NET [Microsoft Docs]. Retrieved from: https://docs.microsoft.com/en-us/dotnet/machine-learning/how-does-mldotnet-work.

Na, N. (2017). Overfitting In Machine Learning: What It Is And How To Prevent It. EliteDataScience. Retrieved from: https://elitedatascience.com/overfitting-in-machine-learning#overfitting-vs-underfitting.

Na, N. (2018). ML.NET - Wikipedia. ML.NET. Retrieved on 2018-05-07 from: https://en.wikipedia.org/wiki/ML.NET.

Navon, R. & Kolton, O. (2006). Model for automated monitoring of fall hazards in building construction. *Journal of Construction Engineering and Management*, 132(7), 733–740.

Pirkl, G., Hevesi, P., Amarislanov, O. & Lukowicz, P. (2016). Smart helmet for construction site documentation and work support. *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct*, pp. 349–352.

Polyzotis, N., Zinkevich, M., Roy, S., Breck, E. & Whang, S. (2019). Data validation for machine learning. *Proceedings of Machine Learning and Systems*, 1, 334–347.

Rehman, S., Mohandes, M. A. & Alhems, L. M. (2018). Wind speed and power characteristics using LiDAR anemometer based measurements. *Sustainable Energy Technologies and Assessments*, 27, 46–62.

Rooney, S., Bauer, D. & Scotton, P. (2006). Techniques for integrating sensors into the enterprise network. *IEEE Transactions on Network and Service Management*, 3(1), 43–52.

Sanni-Anibire, M. O., Mahmoud, A. S., Hassanain, M. A. & Salami, B. A. (2020). A risk assessment approach for enhancing construction safety performance. *Safety science*, 121, 15–29.

Schnaubelt, M. (2019). *A comparison of machine learning model validation schemes for non-stationary time series data*.

Schuldt, S. J., Nicholson, M. R., Adams, Y. A. & Delorit, J. D. (2021). Weather-Related Construction Delays in a Changing Climate: A Systematic State-of-the-Art Review. *Sustainability*, 13(5), 2861.

Shahin, A., AbouRizk, S., Mohamed, Y. & Fernando, S. (2014). Simulation modeling of weather-sensitive tunnelling construction activities subject to cold weather. *Canadian journal of civil engineering*, 41(1), 48–55.

Su, H.-N. & Lee, P.-C. (2010). Mapping knowledge structure by keyword co-occurrence: a first look at journal papers in Technology Foresight. *Scientometrics*, 85(1), 65–79.

Tang, S., Shelden, D. R., Eastman, C. M., Pishdad-Bozorgi, P. & Gao, X. (2019). A review of building information modeling (BIM) and the internet of things (IoT) devices integration: Present status and future trends. *Automation in Construction*, 101, 127–139.

Van Eck, N. J. & Waltman, L. (2014). Visualizing bibliometric networks. In *Measuring scholarly impact* (pp. 285–320). Springer.

Widyantara, H., Rivai, M. & Purwanto, D. (2019). Wind direction sensor based on thermal anemometer for olfactory mobile robot. *Indonesian Journal of Electrical Engineering and Computer Science*, 13(2), 475–484.

Wu, F., Rüdiger, C., Redouté, J.-M. & Yuce, M. R. (2018). WE-Safe: A wearable IoT sensor node for safety applications via LoRa. *2018 IEEE 4th World Forum on Internet of Things (WF-IoT)*, pp. 144–148.

Yadav, S. & Shukla, S. (2016). Analysis of k-fold cross-validation over hold-out validation on colossal datasets for quality classification. *2016 IEEE 6th International conference on advanced computing (IACC)*, pp. 78–83.

Yong, T. & Dol, S. S. (2015). Design and development of low-cost wind tunnel for educational purpose. *IOP Conference Series: Materials Science and Engineering*, 78(1), 012039.

Zhang, T. T., Li, H. & Wang, S. (2012). Inversely tracking indoor airborne particles to locate their release sources. *Atmospheric environment*, 55, 328–338.

Zhao, Z., Pan, Y., Zhao, R., Du, L., Fang, Z., Wu, H. & Niu, X. (2018). Design of a Wind Sensor Based on Cylinder Diametrical Pressure Differences for Boundary Layer Meteorological Observation. *Multidisciplinary Digital Publishing Institute Proceedings*, 2(13), 1511.

Zhou, Y. (2019). Design of a Wind Speed Sensor based on MEMS. *2019 4th International Conference on Mechanical, Control and Computer Engineering (ICMCCE)*, pp. 487–4875.

Zhu, Y., Chen, B., Gu, F., Qin, M. & Huang, Q. (2014). A self-packaged two-dimensional thermal wind sensor based on thermopiles for low cost applications. *Journal of Micromechanics and Microengineering*, 24(7), 075008.

Zou, X., Yue, W. L. & Le Vu, H. (2018). Visualization and analysis of mapping knowledge domain of road safety studies. *Accident Analysis & Prevention*, 118, 131–145.