Smart metering to asset/human tracking for industrial applications

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ABSTRACT: Since practically anything can now be obtained with the push of a button, a seamless logistics procedure is crucial to maintaining the level of convenience that society has become used to. Production facilities are inherently dynamic in the sense that their components are always in flux and subject to deviation from the original plan. As a result, there will be an even greater pressure to enhance various facets of the manufacturing processes. Modern production management requires data positioning inside the industrial system to provide real-time information for tracking and digitizing inputs and outputs. This paper explores the potential of how smart-metering and smart-tracking may be utilized to monitor assets within an industrial context, by means of Real Time Location Systems (RTLS), environmental sensors and an open-source dashboard. Surveys were conducted that consist of Bluetooth Low Energy (BLE), radio-frequency identification (RFID), WiFi, Ultra-wideband (UWB), 5G, and ZigBee technologies. It will also be performed on a number of localisation techniques. The following environmental variables will be monitored: temperature, relative humidity, noise, pressure, light, and carbon dioxide (CO_2). The feasibility of integrating RTLS and environmental sensor outputs into an open-source dashboard to display relevant data was investigated.

Key words: Smart-tracking, Smart-metering, Real-Time Location Systems, Environmental sensors, Internet-of-Things, Industry 4.0, Open-source dashboard.

1 INTRODUCTION

Now that almost everything is easily accessible, the usual level of comfort enjoyed by society relies greatly on a streamlined logistical process. The workings of production facilities tend to be dynamic, in the sense that parts inside the facility are constantly relocating and might depart from the original plan. This means that the need to improve aspects of production processes must adapt with these changes in the facility [1].

Real-time information for the traceability and digitization [2] of resources, production, and goods is necessary for advanced production management systems, and this information comes from the position data within the industrial system [3]. With the indoor positioning system (IPS) being estimated to be worth over US$ 41 billion in 2022, the potential for brand-new and fascinating developing technologies has arrived [4]. Implementation of these technologies, including those related to smart, monitoring, and smart tracking, in factories provides greater visibility into the operation of things on a much larger scale [5][6].

There are two primary kinds of indoor localization techniques which are infrastructure-based and framework-less approaches. Where the infrastructure-based methods use environmental features such as light, sound, and the magnetic field to identify objects in an environment [7] and the framework-less method typically consists of wireless nodes that can be placed anywhere, such as the Ad hoc networks [8].

The measures taken in this paper involve combining data collected from environmental sensors [9][10][11] and Real Time Location System (RTLS) technologies [12][13][14]. The use of environmental sensors produces environmental conditions data such as temperature, carbon dioxide (CO_2), sound, humidity and lights within the designated area, while RTLS tracks the location of the assets in either 2- or 3-dimensions. The information gathered by the environmental sensors and RTLS can subsequently be shown on an open-source dashboard [15].

Different technologies of each aspect of this paper will be delved into further. Their applications and limitations are going to be studied and compared in order to realize the concept. For example, different RLTS systems, communication protocols and other factors will be taken into consideration [17] [18].

Fig. 1: Smart-tracking by utilizing an Indoor Position System [16]

Different types of environmental sensors and how they communicate with each other will also be surveyed. Figure 1 depicts the notion of indoor asset monitoring in an industrial scenario.

This paper aims to answer the primary research question of how smart metering can be utilized to track assets within an industrial application. Practical research on this topic is currently being conducted as well by the department of Design, Production and Management of Twente Universiteit, under the chair of Manufacturing Systems. The research backdrop and aims are presented in Section 1 of this paper, and the topics of smart-tracking, smart-metering, environmental sensors, RTLS and open-source dashboarding are covered in detail in Section 2. The methodology used to carry out this research will be discussed in Section 3, while Section 4 examines the results and limitations of this research.

2 LITERATURE REVIEW

2.1 Smart-tracking

Due to the enormous, unexpected and hazardous investments involved, establishing or modifying production environments necessitates the participation of stakeholders from several disciplines at varying degrees of aggregation [19]. Tracking and monitoring a predetermined environment is not a brand new idea. In a smart factory, for instance, cutting-edge technologies such as cyber-physical systems (CPS) are applied to monitor physical processes by building a virtual environment so that industrial automation may be performed by modular and structured pieces [20].

As an example, chemical plants and factories have also been tracking their production lines for any changes in temperature that can cause harm due to unstable chemicals within different temperature zones [21].

Systematic and regular tracking of construction progress has been often cited as a crucial element of project controls that may assist avoid schedule and budget overruns [22]. By implementing an effective smart-tracking measure in these facilities, companies will be able to get transparency over their logistics management.

2.2 Smart-metering

Smart-metering is a new form of advanced and sophisticated metering instrument that can: record the data of a specific measuring point in intervals; communicate and transfer the information recorded in real time or at least once per day via any communications network to a server; enable two-way communication between the meter and the central system of the company; and do all of the above [6]. A critical challenge is how to use vast amounts of smart-metering data to enhance and boost the system's efficiency and sustainability, where significant research has been undertaken on smart meter data analytics to date [23].

For example, the concept of smart-metering has been a long occurrence in the electricity industry. Big data has the ability to significantly contribute to the optimization of electric power systems and other management choices. In addition, big data increases the strain on data transmission networks and storage expenses [24]. This information may aid in the formulation of marketing strategies and demand side management (DSM) for energy firms [24]. In an ideal scenario, power production and system functioning can be maximized in near real time, energy demand can be reliably forecast, electricity can be dispatched in a timely manner, electricity consumption patterns can be accurately detected, and more efficient pricing mechanisms can be devised [24].

The majority of available literature regarding smart-metering discusses smart-meters for electricity. For the purpose of this paper, smart-metering will be used as a way to monitor the ever changing elements within the industrial environment. The data gathered by means of RTLS and environmental sensors will be used to find the most efficient way within an industrial application.

2.3 Real-Time Location Systems (RTLS)

A critical component of smart factories is the ability to know what goes on inside a factory, in real time. Data gathered on where assets are, their status and movements is important, especially considering thousands of elements constantly changing within the smart factories. RTLS provides the necessary feedback in 2- and 3-dimensions, and they are applicable for both indoor and outdoor [3].

Real Time Location System is not a piece of technology or mechanism, it is merely a method to accurately locate and manage assets. One important factor of RTLS is the time something is tracked [25]. RLTS will enable real-time analysis and the development of multiple state maps to monitor operations, machinery, personnel and resources on the production floor [13]. RTLS has made farming, warehousing, air travel and so many more reach their full potential. Tag based RTLS is the most established in manufacturing applications [12][14], therefore it will be one of the main focuses of this paper.

2.3.1 RTLS composition

Acquiring data through RTLS consists of three steps [26] that can be taken: tracking the path of assets using tags and anchors, sending tracked data from the RTLS to the designated server and wrangling and storing them in the database.

The aforementioned anchors can be planted within the desired environment while the tags send and receive signals from them [14][12]. Most RTLS tags are capable of both position sensing and data storage capability [27]. There are different types of tags, and these tags can be planted on machines, materials, products and even human assets [12][14][26][27].

2.3.2 Localization in RTLS technologies

Several algorithms are used to precisely calculate the position of these tags with respect to the anchors [17]. This section will describe and compare the different types of algorithms [17][14]:

- **Time of Flight (ToF) or Time of Arrival (ToA):** Calculates the distance between the transmitter and the receiver by maximizing the signal propagation time [17]. To find the distance to a node, it takes the speed of light times the amount of time from when the signal is first dispatched [14]. Within the context of multipath indoor conditions, the resolution of ToF estimation grows larger as the bandwidth grows [28]. ToF is able to achieve three-dimensional tracking by means of combining sets or tags and anchors [14].
- **Return Time of Flight (RToF):** Measures the time taken for the transmitter to send a signal to a receiver and for time to be sent back to the transmitter (transmitter-receiver-transmitter) [28]. The necessity for reasonable synchronization between the transmitter and receiver is an advantage of RToF. The same factors affect RToF's accuracy estimation as ToF [17] (sampling rate and bandwidth), but slightly worse because RToF does twice the work ToF does.
- **Received Signal Strength (RSS):** Among the several methods of indoor localisation, this is one of the most straightforward and popular [29] [14]. Signal strength is used to calculate the distance between a tag and a transmitter [17][30]. Although implementation is straightforward, non-line-of-sight precision is inadequate [14].
- **Angle of Arrival (AoA):** Utilizes the antennas at the receiver to generate an approximation of the angle by using and calculating the time difference of arrival at the various antennas [17]. Several antennas are needed to accurately measure angles throughout an entire factory, and cost increases as accuracy increases with it [14].
- **Time Difference of Arrival (TDoA):** Measures signal that travels from a transmitter (tag) to receiver, which is very similar to ToA [31]. The signal that is delivered concurrently from a number of anchors, as well as the difference in time that is received, are both factors that are monitored, followed by the use of a time synchronization method between access points to calculate the TDoA [32]. TDoA is very accurate when used alongside UWB as the communication protocol [14] [32].

• **Phase Difference of Arrival (PDoA):** Anchor equipped with two antennas delivers signals to the item, and the difference in phase between the antennas may be utilized to compute where the tags is placed in relation to the anchor [14]. It is possible to determine the real-time positions of a large number of objects [14].

2.3.3 RTLS communications protocols and technologies

When a company's objective is precisely specified, several RTLS communication protocols can be chosen depending on the application [25]. This section will delve into the different types of communication protocols and technologies to compare them with each other. These technologies are [14][17]:

• **Radio Frequency Identification (RFID)** depends on two key elements: RFID tags and RFID readers [7]. RFID does this by making use of electromagnetic transmission and a combination of readers in order to locate the tags that are nearby [17]. A transceiver is included within the reader to read the data generated by the tags and send radio frequency signals [14]. These tags may be divided into passive and active categories: active tags are powered by a battery and passive tags are generally powered by received radio signals [7]. Both active [33] and passive [34] can be used to estimate the location of a certain object. RFID tags can also be combined with environmental sensors [35] and other sensor technologies to track indoor positioning [36].
• **WiFi** (or the IEEE 802.11 standard) is largely used in order to provide various devices in private, public and commercial settings the ability to participate in networking activities and to establish connections to the Internet [17]. WiFi is quite common in indoor positioning and can be used in conjunction with a variety of other localization techniques to ascertain the location of assets [14].
• **Bluetooth** (or IEEE 802.15.1) consists of the physical and Media Access Management (MAC) layers (more on this in the next subsection) which are the requirements for connecting various wireless devices, whether they are stationary or mobile, inside a defined space [17]. One of the most recent advancements in IoT technology is called Bluetooth Low Energy (BLE), and it is well fitted for hyper low energy sensors that operate on tiny batteries. Bluetooth Low Energy (BLE) has shown to be a viable alternative to IPS, offering low-cost deployment in addition to a decent level of precision [37].
• **ZigBee** (or IEEE 802.15.4 standard) is concerned with the physical and MAC layers for low cost, low data rate and energy efficient personal area networks [38]. The communication system is more economical and user-friendly than existing short-range wireless technologies such as Bluetooth and Wi-Fi [39] [40]. While Zigbee is advantageous for WSN sensor localization, it is not widely accessible on most user devices, making Zigbee unfavorable for user indoor localization [17].
• **Ultra-Wideband (UWB)** is a wide-band technology that makes use of frequency channels that have a bandwidth of at least 500 MHz, therefore avoiding interference with other radio-frequency systems [14]. UWB is a preferred candidate for IPS development because of its characteristics, including extremely low power consumption, efficient penetration through thick materials and reduced sensitivity to the multipath effect due to the short pulse length of UWB signals [7]. Because of the large bandwidth connected with this technology, timestamp signals have a greater precision, which means multipath (e.g. interferences generated by signal reflections resulting to numerous signals) is recognized more accurately. [14].
• **5G** is the fifth generation of digital wireless communication systems and it allows high data rates. It has been hypothesized that these revolutionary 5G technologies are advantageous for wireless positioning, which has attracted a significant amount of study on positioning based on 5G NR signals [41].

The criteria for comparing different RTLS systems will be the same criterias used in [14], as these criterias give a comprehensive and summarized insight into the subject. These criterias are:

• **Range:** BLE and passive RFID work well for short distances, while UWB and WiFi has a higher reach [14]. Since 5G is not limited by physical boundaries, it has the potential to have a greater range.
• **Accuracy:** It has been proved that new millimeter-wave technology, which is now being investigated for use in 5G communications networks, will be able to deliver strong centimeter-level accurate indoor localization [42]. UWB also has one of the best

accuracy compared to the other technologies.
• **Existing infrastructure:** RFID and UWB will require additional infrastructure to be built within the system, while the rest can be integrated into an already existing infrastructure.
• **Availability:** It is mentioned in [14] that UWB and 5G are not readily standard features at the time of article's publication. Nowadays, both UWB and 5G can be accessed openly in the market. This is also true for WiFi, GPS and Bluetooth.
• **Indoor usability:** All mentioned technologies has capabilities of indoor applications.

2.3.4 RTLS data

In recent years, breakthroughs in data gathering technologies, enhancements in data mining techniques and a decrease in the price of development kits have spawned many industrial applications. Collecting such data in a coordinated way is not a simple operation. Multiple businesses provide position data collection and interpretation services using RTLS technology with the accuracy still doubtful [43].

To extract usable data from location information, manufacturing process zones must be specified [3]. By dividing the factory into zones, features of each zone may be retrieved. As an example, these characteristics may be separated into stations where the movements and locations of certain assets are anticipated [14]. Andras Racz-Szabo et al. (2020) illustrated the concept of mapping an environment into stations in their research, which can be seen in Figure 7 in the appendix.

Line-based diagrams or maps, sometimes known as spaghetti diagrams, are created as a means of further visualizing the data [44]. Color-coding items, employees or technical resources allows for more precise tracking of their whereabouts at any given moment [45]. Using the information gleaned from the Spaghetti diagram, wasteful processes may be identified, employees can be reduced and work organization and station layout can be altered to improve efficiency [45].

As an example, the trademarked ATLAR-5D system developed by Quarion is used to effectively monitor inventory in a manufacturing plant. To do this, UWB anchors are used to track down items that have been tagged [44]. Using a rate of up to 50 times per second, the system captures the current position of tagged items.

Figure 6 in the Appendix depicts the paths taken by forklifts, workers and other machinery using Quarion's technology. The blue lines represent the path least taken, while the red lines represent the path most taken [44].

2.4 Environmental sensors

Environmental sensors are the sensor chosen to track and gather data in real time for the purpose of this paper. Environmental sensors may be referred to interchangeably as sensors for the remainder of this work. This sensor system is expected to record temperature, occupancy, pressure, indoor air quality, noise, light, carbon dioxide emission and more. This sensor system is able to work alongside intelligent systems, which can self-monitor and respond to dynamic conditions that optimizes safety and performance [11]. It can be referred to as wireless sensor networks or WSN [46]. Nowadays, general environmental sensors can be found in everyday applications. With the growth of Internet-of-Things (IoT), smart sensors have been widely used in an array of applications. Monitoring the quality of drinking water [9], maintaining a smart garden with Edyn [47], a family pocket-sized gas measuring sensor [11] and among other things.

This sort of sensor (smart sensor) is distinguished by (a) low energy consumption, adaptability and autonomy, (b) simplicity of integration with servers, (c) longevity and dependability of IoT platforms and sensors and (d) simple installation and deployment of sensor nodes [9]. In addition to the physical sensor element, the whole sensor system may additionally include analog-to-digital signal processing and transceivers [48].

2.4.1 Environmental factors

This paper proposes to look at different environmental factors that are quantifiable. These factors are:

• **Carbon Dioxide (CO_2) concentration**: Indoor air quality sensors such as *ELRO* detect CO_2 in Particles Per Million (PPM) [49]. In the context of

IPS, CO_2 sensors have been regarded as a secondary source of data after other types of sensors [50]. CO_2 concentration has been utilized to determine building occupancy, but it is not the ideal method for detecting stationary things [51].

• **Humidity**: Humidity is a physical quantity that is regularly measured and has great importance for various applications [52]. Relative Humidity (RH) sensors play a crucial part in the state-of-the-art environmental regulation system, being used in applications such as monitoring air-quality of a certain working environment [53].

• **Light**: Photoelectric sensors detect the change of light from the emitter to the receiver and convert light into an electrical output [54]. The technological advancements of this type of sensor has been so far that it is able to detect small inorganic molecules and heavy metal ions in polluted water [55].

• **Noise**: Noise level within a factory plays an important role when conducting a smooth sailing operation, which can be tracked using noise sensors [56]. Monitoring and mapping by means of capturing noise within a set environment has been proven successful [57].

• **Pressure**: Utilizing pressure sensors as a detecting method, by means of detecting minute pressure changes with a high accuracy, for some time [58]. A study to see whether low-cost Micro Electro-Mechanical Systems (MEMS) pressure sensors can be useful for indoor tracking purposes was conducted in 2016, which was proven successful [59].

• **Temperature**: Thermal sensors have been used to accurately track humans in different applications. In order to determine whether or not a space is occupied, a change in the environment's temperature can be used to determine this [60]. In 2019, an experiment by Qu and Yang [61] was deemed successful when thermopile sensors were used to track multiple human subjects within an indoor space.

2.4.2 Environmental sensor communication protocols

The data collected by the sensors must be successfully communicated to the sink node. Figure 2 illustrates the concept of multiple sensors in a WSN, sending and receiving data to and from the head of the cluster, where the data then goes to and from the sink node to be wirelessly accessible by the users [62]. Some of the protocols used by the sensors to communicate with each other are similar to that of the RTLS. Protocols such as Wi-Fi, UWB, Bluetooth and ZigBee can all be used [63][64][65], but there are other protocols such as: SigFox [66], Z-wave [67], NFC [68] and others.

A protocol stack facilitates collaboration between sensor nodes by combining routing awareness, incorporating data into networking protocols, communicating power effectively across the wireless channel [69]. As seen on Figure 8 in the Appendix, the protocol stack is composed of layers and planes.

The book *Wireless Sensor Networks*, written by M.A. Matin and M.M. Islam in 2012 [69], gives an overview of the the wireless sensor network. Depending on the requirements of the sensing activities, many forms of application software may be developed and employed at the **application layer**, where it hides the underlying hardware and software from the user. If the application making use of the sensor networks needs continuous data transfer, the **transport layer** may assist ensure that this happens. The **network layer** is in charge of sending the information provided by the transport layer, which consists of customized multi-hop wireless routing protocols between the sensor nodes and the sink. Frame detection, Media Access Management (MAC) and error control are all tasks that fall within the purview of the **data link layer**. The MAC protocol must be power-aware and capable of minimizing collision with neighbors' broadcast due to the loud environment and the potential mobility of sensor nodes. The requirements for modulation, frequency selection, data encryption, transmission and reception are met by the **physical layer**.

2.4.3 Environmental sensor positioning

A literature review article by Alma Mena et al. (2022) presents an overview of how environmental sensors are used to identify occupancy, the locations chosen for tests, information regarding the positioning of sensors, features of datasets and models/algorithms [70]. It included 93 research on sensor-based occupancy estimations from 2009 to 2021. For areas larger than 100m^2, 19 studies had CO_2 sensors utilized to estimate occupancy, 13 utilized temperature sensors, 11 utilized relative humidity sensors, two utilized pressure sensors, one utilized noise sensor and six utilized light sensors [70].

For ten to 400 occupants, six studies utilized CO_2 sensors, 11 utilized temperature sensors, eight utilized relative humidity sensors, three utilized pressure sensors, six utilized noise sensor and four utilized light sensors [70]. The amount of sensors employed in each study varies. Table 1 presents the information in a more comprehensible format.

Table 1: Quantity of environmental sensors planted per research and sensor type [70]

Type	**Area >100m^2**	**10 - 400 Occupants**
Carbon Dioxide (CO_2)	19	6
Humidity	11	8
Light	6	4
Noise	1	6
Pressure	13	3
Temperature	13	11

The article states that a correlation between the number of deployed sensors and the size of the measured environment can be seen. However, the number of occupants itself does not quite affect the number of sensors deployed. Furthermore, the four most prominent sensor locations were in the middle of the room, near a door, mounted on the wall and close to the occupants, respectively. Where the three most prominent height placements of the sensors were 100cm, 150cm and 0cm from the ground, respectively. These findings will be considered in the context of the deployment of environmental sensors in this paper.

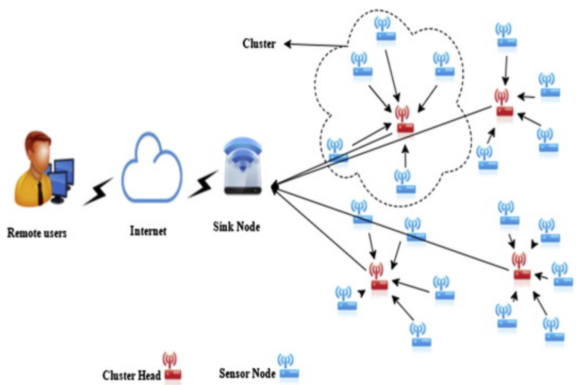

Fig. 2: Wireless network system [46]

2.4.4 Environmental sensor data

Locations of assets will be determined using the data that was gathered from the various environmental sensors. As the previous subsection suggests, when the sensors are positioned as desired, producing the necessary data poses no difficulty.

Figure 3 is an example of a temperature sensor heatmap displaying clustered sensor locations and temperature measurements in a greenhouse by Reginald Fletcher and Daniel Fisher (2021) [71]. Twelve sensor nodes were constructed and deployed at various positions inside a greenhouse in order to analyze sensor placement and environmental parameter variability, while the sensors were evaluated using data obtained during February 2019 [71].

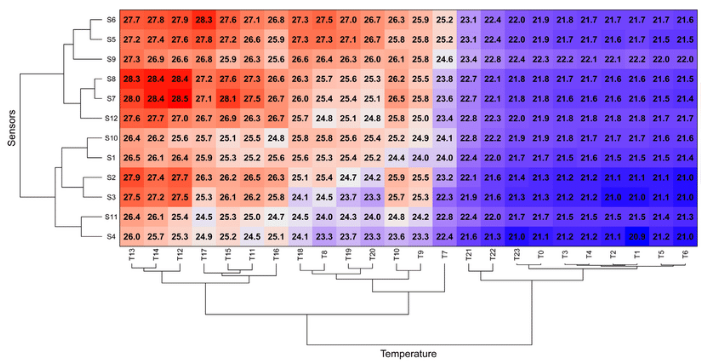

Fig. 3: SHT31D temperature sensor heatmap clustered on sensor location and temperature readings in the greenhouse [71]

By deciding which environmental factors are desired as data features, users may concentrate on what information is useful. Temperatures, humidity, CO_2 emission, sound and light are all readable data that can be translated and visualized.

Multiple machine learning models that forecast occupancy, such as the conditional random fields (CRF), Markov model, k-Nearest Neighbor (kNN), etc., have been exhaustively studied, but are outside the scope of this study[72][73][74].

2.5 Handling and visualization of data

2.5.1 Data fusion

The data collected from the various technologies must be processed according to the user's requirements, in order to be interpreted by a human operator. Because RTLS and environmental sensors serve distinct purposes, one must devise a method for combining data from both systems and sensors into a usable output for the operator. These data must be gathered in real-time, cleaned and preprocessed before they can be used for analytics.

Herein lies one of the roles of feature engineering. Feature engineering is the process of changing a dataset's feature space to enhance predictive modeling performance [75]. A feature is a cohesive and distinguishable collection of system capabilities that helps define the system from the user's viewpoint [76]. They are significant aspects in the field of machine learning, but in the scope of this paper, the characteristics will be the means through which the data wanted will be utilized.

Similar to predicting occupancy, existing machine learning methods such as the Markov model, k-Nearest Neighbor (kNN), Bayesian Networks, etc., that enable the merging of RTLS data with environmental sensor data do exist, but are outside the scope of this paper[77][78].

2.5.2 Open-source dashboard

The data visualization field has been studying the problem of how to effectively visualize high dimensional data for over three decades [79]. Ease of implementation, sufficient localization accuracy, scalability, manageable system cost and low computing complexity are all desirable qualities in an IPS [4]. The gathered data needs to be processed and visualized by human operators by building an open-source dashboard.

There are a few different ways to describe what exactly a dashboard is. Combining definitions from other literature, a dashboard can be described as a single screen graphical interface that shows the results of significant data collecting via a consolidated set of indicators [80] [81] [82]. Open-source dashboards are dashboards that may be customized and/or modified by users as required [83].

The goal of open-source dashboards is to provide everyone with a stake in a problem a comprehensive view of the information they need to make an informed choice [19]. Stockholm, the capital and largest city in Sweden, has incorporated several dashboarding methods to analyze how dashboards can process the big data collected and use said data to make smart decisions for *i-cities* [84].

Figure 9 in the Appendix is an example of an open-source dashboard by one of the leading companies in the field. It displays all the features the user has chosen to process and monitor.

Indicative of a well-designed dashboard is the availability of information, models, simulations and methodologies that enable all stakeholders to address certain problems or topics inside the production environment [19]. Effective feedback by a dashboard must come from basic learning that was determined by the builder or user of said dashboard [85]. New sensor data transmission protocols and data formats, new visualization styles and enhanced dashboard representations of displayed sensors are needed when a large number of sensors evolve constantly. Simply defined, things must be freely added and removed from the dashboard for it to be considered open-source.

2.5.3 Challenges of dashboarding

Authors van Elten et al. (2022) [80] highlighted three recurring difficulties that were encountered when developing performance dashboards that matched the twin needs of being relevant to pilot partners and allowing for an evaluation of goals and accomplishments. These three challenges were pleaded to be reflected upon and navigated:

(1) Managing divergent stakeholder perspectives and expectations, (2) Managing collection of timely and meaningful data and (3) Managing diverse dashboarding requirements and objectives.

This motivates the creation of dynamic dashboarding solutions by author Sander Vanden Hautte et al. (2020) [86]. In contrast to fixed-structure dashboard applications, they allow users to construct visualizations on-demand and without hard-coded sensor connections [86]. The current state of the art in dynamic dashboarding does not support the frequent additions and removals of sensors that must be monitored; these changes must still be specified by a user during installation or runtime [86]. In addition, the user is presented with an abundance of sensors, aggregations and visualizations to pick from, which may sometimes lead to the creation of incomprehensible dashboard widgets [86].

3 METHODOLOGY

3.1 Case use of concept

The objective of the project is to effectively track and monitor a variety of assets; including equipment, people and goods, throughout a production facility. There are steps that must be made in order to successfully realize the concept discussed above. First, a hypothetical industrial application and environment must be established for this paper, which will be referred to as *Jages Factory* from this point onwards.

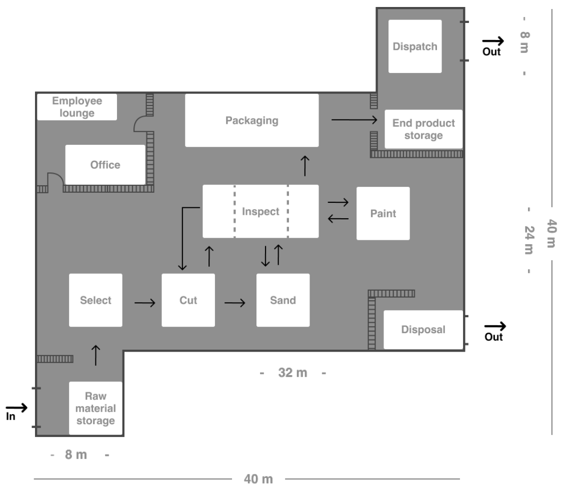

Fig. 4: *Jages Factory*'s floor plan

Jages Factory is a production facility that deals with the production of strictly wooden baseball bats, which can be seen in Figure 10 in the appendix. This paper's concept will be applied onto one the production floors, which consists of human workers, automated guided vehicles (AGVs), forklifts and machines. This production floor will be divided into several working zones, illustrated in Figure 4. The size of this factory is $832m^2$.

The functions of these zones are as follows: raw material storage, material selection station, cutting station, sanding section, inspection station, paint and design station, packaging station, finished product storage and dispatch. There is also an employee station that consist of a lounge and offices. Each station will consist of several human workers, stations and machines, while AGVs and forklifts will be used to transport workers and materials throughout the facility.

Different RTLS technologies and environmental sensors will be compared to fit the need of smart-metering and smart-tracking within the production facility. Table 7 in the appendix were created as a means of simplifying things and facilitating the decision-making process.

3.1.1 Weighted average calculation of RTLS technologies

To simplify it a step further, a weighted average will be made to compare each RTLS technology. The assigned weight factors are based on the compilations of literature reviewed in Section 2, with 1 being the lowest score and 5 being the highest. Table 2 shows the weighting factor for RTLS. Equation 1 defines the weighted average (WA) [87]:

$$WA = \frac{\sum_{i=1}^{n} Assigned\ weight * weighting\ factor}{\sum_{i=1}^{n} weighting\ factor} \tag{1}$$

Table 2: Weighting factor assigned to each characteristics for RTLS

RTLS	
Factors	Weighting factor
Accuracy	5
Max. Throughput	4
Max. Range	4
Existing Infrastructure	3
Indoor Usability	5
Availability	3

3.2 Implementation of RTLS technologies

Implementation of RTLS technology will be contingent on a number of variables. These aspects must be explored in more depth and compared to ensure that the best option is selected. This may be performed using the weighted average calculation for each technology.

Table 3: Weighted average of RTLS technologies by communication protocol

RTLS		
Technology	Weighted average	References
BLE	3.33	[14],[43]
RFID	3.48	[14],[43]
WiFi	3.24	[14],[43]
UWB	3.95	[14],[43]
ZigBee	2.86	[39],[40]
5G	4.36	[41]

Results from Table 3 indicate that 5G is the best option, followed by UWB and RFID tags. Due to the lack of research on 5G as RTLS, ultra-wideband will be selected for the proposed system. Specifically, an UWB system utilizing tags and sensors will be selected.

3.2.1 UWB system placement

UWB anchors will be installed all around the factory, while UWB tags will be implanted on vehicles (AGVs and forklifts), pallet racks (where the assets/products are stored, as seen on Figure 11 in the Appendix) and workers. Priority for the anchor placements will be given to walls where there are pathways, such as surrounding employee stations (lounge and offices), finished product stations (storage and dispatch) and disposal.

The position of these UWB tags will be calculated by means of Time Difference of Arrival, based on Table 10 in the Appendix. The scalability of UWB tags is one of the advantages of TDoA. The data acquired by the anchors is transmitted to the dashboard in order to calculate the specific location of the tags, by means of WiFi.

3.3 Implementation of environmental sensors

The environmental sensors will be evaluated based on several factors. The output, usage and communication protocol that may be utilized with each type of sensor are compared in Table 4. In context of usage, the proposed concept will incorporate environmental sensors that can measure CO_2 emissions, noise, pressure (the strain gauge), relative humidity and temperature. This These factors were selected primarily based on the reviewed literature [70].

Table 4: Comparison of different environmental sensors

Sensor type	**Output**	**Usage** [73],[74]	**Commun.** [63][64][65]
CO_2	PPM	Environmental Occupancy	BLE, WiFi, ZigBee
Humidity	Rel. %	Environmental	BLE, WiFi, ZigBee
Light	Js	Environmental	WiFi, ZigBee
Noise	dB	Environmental Occupancy	BLE, WiFi, ZigBee
Pressure	Pa	Occupancy	BLE, WiFi, ZigBee
Temp.	Celcius	Environmental	BLE, WiFi, ZigBee

Furthermore, by utilizing the weighted average computation in Table 3, BLE edges out WIFI as the preferred communication protocol between the sensors. Each of the sensors will have their own MAC address, which allows them to be configured into the dashboard.

3.3.1 Environmental sensors placement

The placement of environmental sensors will be crucial to the concept's success. Table 5 shows the proposed amount of sensors deployed per type of sensor, while Table 9 in the appendix expands on which sensor type is deployed at particular stations. These sensors will be placed either on the ground and/or around 100 - 150 centimeters off the ground, per [70].

Table 5: Placement of environmental sensors throughout the factory

Sensor	**Amount dispatched**
CO_2	14
Humidity	2
Noise	2 + per machine
Pressure	per working area, per pallet rack
Temperature	5

3.4 Data handling and visualization

The output from UWB tags will be in real-time and the data from environmental sensors will be a time series. Merging the two datasets will require feature engineering to pinpoint what is useful and what is neglectable. The RTLS data does not need further pre-processing since it will provide the real-time location of each anchor and will be utilized to supplement the sensor data.

The sensors will be labeled with names such as ”node_1, node_2, ... , node_n” and organized by their respective stations Thus, a heatmap can be generated from each station and the data from each station may be readily interpreted. The Conditional Random Field (CRF) predictive model is used to generate occupancy estimates from the sensors' output in real-time, as it was carried out in [73]. The integration of both RTLS and environmental data can be processed with different machine learning algorithms, like ones proposed in [77] and [78].

3.4.1 Dashboarding

One of the reasons this paper proposes an open-source dashboard is so that users can combine all of the outputs from both RTLS and environmental sensors with various communication protocols, functions, etc. into a single legible and customizable result.

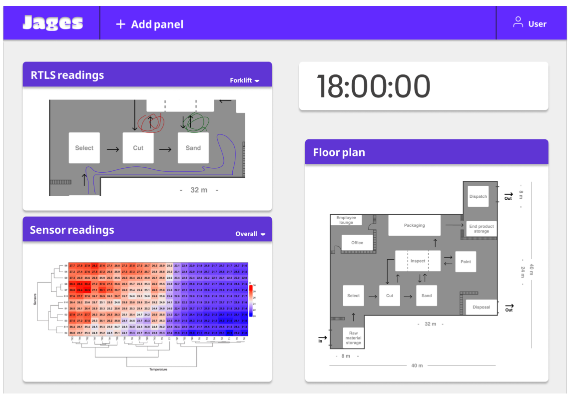

Fig. 5: Proposed design of the open-souce dashboard

The proposed design for the open-source dashboard is illustrated in Figure 5. The dashboard displays the time of day, output from the UWB RTLS tags and anchors, output from the environmental data and an overall layout of the factory.

This dashboard's widgets may be added and deleted as desired. The sensor display widget can be sorted by sensor, per station or as a whole. The spaghetti diagram is shown by the RTLS widget. It may also display the general movement inside the factory, each monitored tag and/or asset, as well as the location of the anchors. The user may modify the factory's overall view based on timestamps as necessary. All of this data may be retrieved in the format of choice and will be valuable for factory operation.

4 DISCUSSION AND LIMITATIONS

Several limitations were encountered while writing this paper. With any tracking technology, privacy becomes a concern. The proposed concept and the acquired data will not reveal any personal information about manufacturing employees, hence protecting their privacy.

The impacts of multipath signals could have been examined more in the methodology section. This has major implications for indoor localisation, namely precision. To acquire a precise estimation of the position, complicated signal processing methods and the elimination of multipath signal effects are essential.

The machine learning algorithms for occupancy estimate and data fusion were not addressed in depth; which is something that should be addressed in future studies regarding this subject. This is also similar to power consumption of both the environmental sensors and RTLS technologies.

The incorporation of error measurements to verify the precision of sensor occupancy estimates were not addressed. This would have further complicated the study and been beyond the scope of the paper. The cost of the proposed concept was also not addressed in this study, despite the fact that it is a significant element in determining whether or not the concept would be deployed. The paper might also have benefited from more study on sensor clusterings and BLE devices.

Lastly, insufficient research on 5G are currently accessible, which makes one question how interesting the future will be when 5G can be adopted in place of WiFi, BLE or UWB.

5 CONCLUSION

The paper proposed to examine the possibility of how smart-metering and smart-tracking may be applied to monitor assets within an industrial setting, by means of Real Time Location Systems (RTLS), environmental sensors and an open-source dashboard. The weighted average of Bluetooth Low Energy (BLE), radio-frequency identification (RFID), WiFi, Ultra-wideband (UWB), 5G and ZigBee technologies were calculated to find the best RTLS technology option. Localization approaches were explored to determine the optimal method for occupation prediction and data fusion. It is suggested to monitor the following environmental parameters: temperature, relative humidity, noise, pressure, light, and carbon dioxide (CO2). Both RTLS and environmental sensor outputs can be included into an open-source dashboard to display relevant data that can be used to perform smart-metering.

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7 APPENDIX

Tables

Table 6: Abbreviations used in this paper

Abbreviation	Definition	Abbreviation	Definition
AGV	Automated Guided Vehicle	IoT	Internet of Things
BLE	Bluetooth Low Energy	MAC	Media Access Management
CO2	Carbon Dioxide	PPM	Particles Per Million
CRF	Conditional RandomField	RFID	Radio-frequency identification
DSM	Demand Side Management	RH	Relative Humidity
DSO	Distribution Systems of Operation	RTLS	Real-Time Locating Systems
GPS	Global Positioning System	UWB	Ultra-Wideband
IEEE	Institute of Electrical and Electronics Engineers	WSN	Wireless Sensor Network
IPS	Indoor Positioning System		

Table 7: Comparison of different RLTS technologies by communication protocol

	BLE	RFID	WiFi	UWB	ZigBee	5G
Dynamic accuracy	100m	0.9 - 1.6m	1 - 3m	0.08 - 0.2m	1.5 - 2 m	0.2 - 0.8 m
Maximum throughput	24 Mbps	640 Kbps	400 Mbps	460 Mbps	250 Kbps	~ 641Mbps
Maximum range	10 m	100 m	60 meter	10 - 20m	10 - 100m	12 m - 200m outdoor
Existing infrastructure	No	Yes	No	Yes	No	No
Indoor positioning usability	Yes	Yes	Yes	Yes	Yes	Yes
References	[14],[43]	[14],[43]	[14],[43]	[14],[43]	[39],[40]	[41]

Table 8: Calculations of weighted average for RTLS by communication protocol

	Weighting Factor	**BLE**	**RFID**	**WiFi**	**UWB**	**ZigBee**	**5G**
Dynamic accuracy	**5**	2	3	2	5	2	4
Maximum throughput	**4**	3	2	4	4	1	5
Maximum range	**4**	2	4	3	2	4	5
Existing infrastructure	**3**	5	3	5	3	5	5
Indoor positioning usability	**5**	5	5	3	5	3	3
Total	**21**	70	73	68	83	60	92
References		[14],[43]	[14],[43]	[14],[43]	[14],[43]	[39],[40]	[41]

Table 9: Placement of environmental sensors throughout the factory

Station	Sensor type	Amount dispatched	Station	Sensor type	Amount dispatched
Cutting	CO_2	1	Packaging	CO_2	1
	Noise	per machine		Pressure	per pallet racks
Dispatch	CO_2	2	Paint	CO_2	1
	Noise	1		Noise	per machine
Disposal	CO_2	1	Product storage	Humidity	1
Employee	CO_2	2		Temperature	1
(lounge offices)	Temperature	2	Raw storage	Humidity	1
	CO_2	1		Temperature	1
Inspection	CO_2	3	Sanding	CO_2	1
	Noise	1		Noise	per machine
	Temperature	1	Selection	CO_2	1
				Pressure	per working area

Table 10: Comparison of localization methods

RTLS Localization			
Method	Advantages	Disadvantages	Ref
ToF/ToA	3D tracking by using sets anchors	Lower resolution	[14],[17],[28]
RToF	Reasonable synchronization	2x the work ToF does	[17],[28]
RSS	Straightforward and available	Not precise when there isn't Line of Sight (LoS)	[14],[17],[29],[30]
AoA	Clock sync not needed	Uses too many antenna	[14],[17]
TDoA	Accurate with UWB	Necessity to sync all base stations	[14],[31],[32]
PDoA	Can detect large number of things	Complex hardware and multifrequency carrier signal	[14]

Figures

Fig. 6: Spaghetti diagram of assets movement by *Quarion* [44]

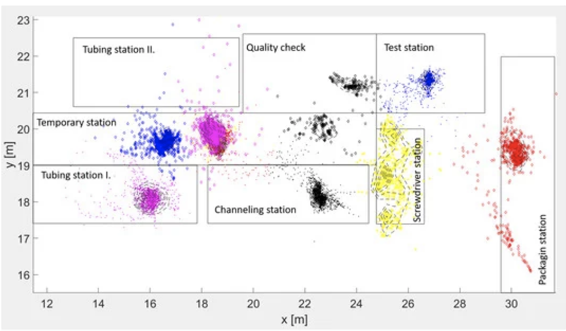

Fig. 7: The production layout with seven pre-defined workstations [3]

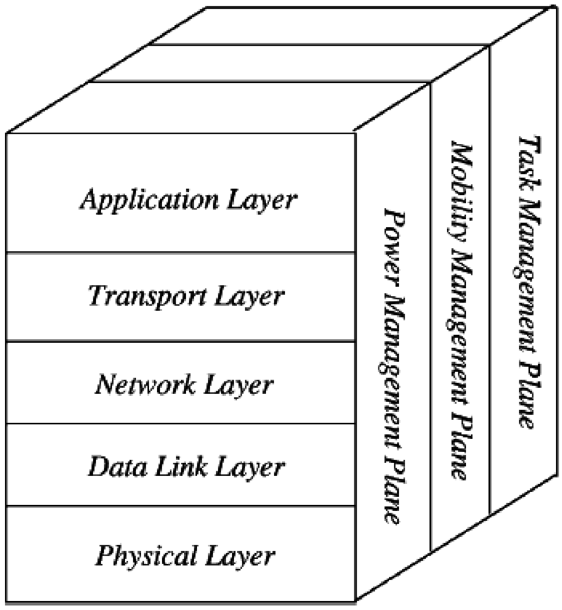

Fig. 8: Wireless Sensor Network protocol stack [69]

Fig. 9: Open-source dashboard by Freeboard

Fig. 10: A wooden baseball bat by Winston Chen, from *unsplash.com*

Fig. 11: Pallet racks by Krisana Nakajo, from *unsplash.com*