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Energy efficient LoRaWAN for Industry 4.0 Applications

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***Abstract*—Thanks to its inherent capabilities (such as, fairly long radio coverage with extremely low power consumption), LoRaWAN can support a wide spectrum of low rate use-cases in the industry 4.0. In this paper, both plain and energy harvesting industrial environments are considered to study the performance of LoRa radios for industrial automation. In the first instance, a model is presented to investigate LoRaWAN in the industry 4.0 in terms of battery life, battery replacement cost, and damage penalty. Then, the energy harvesting potential, available within an industry 4.0, is highlighted to demonstrate the impact of harvested energy on the battery life and sensing interval of LoRa motes deployed across a production facility. The key outcome of these investigations is the cost trade-off analysis between battery replacement and damage penalty along different sensing intervals which demonstrates a linear increase in aggregate cost up to £1500 in case of 5 min sensing interval in plain (non-energy harvesting) industrial environment while it tends to decrease after a certain interval up to five times lower in Energy Harvesting (EH) scenarios. In addition, the carbon emissions due to the presence of LoRa motes and the annual CO_2 emission savings per node have been recorded up to 3 kg/kWh when fed through renewable energy sources. The analysis presented herein could be of great significance towards a green industry with cost and energy efficiency optimization.**

***Index Terms*—Industrial automation, cost and performance evaluation, carbon savings in industry 4.0, energy harvesting, Industrial IoT, LoRaWAN.**

I. Industrial Internet of Things and the fourth industrial revolution

Industrial Internet of Things (IIoT) [1] is a recent wave of connectivity and communication technologies that is being predicted as the game changer in redesigning and reshaping the concept of a smart industry witnessing the new industrial revolution. IIoT introduces a set of standards [2], [3] (e.g, high powered-wireless acess, low cost wireless access, and low power wide area) to enable the connectivity of a wide range of manufacturing equipment to a web-based network and integrates this data for timely decision making [4]. IIoT connects a wide range of sensor devices deployed across the production line to different analytic systems inducing the ultimate performance improvement that can lead towards billions of dollars of savings [5].

Due to their distinct features to meet radio coverage, scalability, and energy requirements for the Industry 4.0 paradigm, Low Power-Wide Area Network (LP-WAN) [6] are considered the trend setters in the evolution of wireless communications. A plethora of LP-WAN technologies are out in the market these days that include: Sigfox, Long Range Wide Area Network (LoRaWAN), NarrowBand Internet of Things (NB-IoT), DASH7, LTE-M1, Ingenu, and Weightless to name a few [6]. Among them, LoRaWAN [7], [8], Sigfox and, Weightless have already been proposed suitable for most of the Machine-to-Machine (M2M) communication scenarios in IIoT use-cases because of their common characteristics (such as, low power consumption, high scalability with extended radio coverage, and simple/low-cost network infrastructure) [9].

Despite several low power technologies have recently been introduced to cater IIoT use-cases, energy is still one of the major challenges for this kind of applications. Energy exhaustive operation of sensor nodes (also known as *motes*) installed within a harsh industrial environment or inaccessible places (e.g., in many industrial monitoring use-cases) makes it impractical to replenish the batteries frequently. Moreover, these batteries are an expendable resource with adverse environmental effects. On the other hand, an optimal sensing interval to generate alerts can well avoid the fast battery drainage but, sometimes, even a slight latency in popping-up an urgent alert costs a bulk of damaged products wasting the useful resources at the production line. The situation becomes even more critical when the production costs of the manufactured products are significantly high and timely detection of various anomalies at different production stages can avoid huge financial losses for a smart industry. However, choosing between the energy optimal operation and the continuous monitoring during the production process, being the two contradictory goals, involves a narrow line trade-off.

To bridge this gap, the present manuscript extends [10] with the following contributions:

- The presented model evaluates the feasibility of LoRaWAN for plain and energy harvesting industrial environments.
- The lifetime of Long Range (LoRa) monitoring devices is calculated considering different sensing intervals and then the impact of these intervals is studied on the lifetime of LoRa monitoring nodes.

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- Two significant operational costs (i.e., battery replacement and damage penalty) are assessed and the optimal sensing interval is suggested.
- The renewable energy potential in industrial environment is exploited to feed LoRa nodes and a socio-economic analysis is presented.
- The CO_2 emissions are evaluated due to the presence of LoRa end-nodes and total emission savings are highlighted in case of energy harvesting LoRa deployments.

The present contribution will focus on the LoRaWAN architecture, but the developed model can also be extended to apply to other LP-WAN standards with slight customization.

This manuscript is outlined as follows: Section II summarizes the current state-of-the-art and provides a comparison of the available LP-WAN options. Section III presents a model to evaluate the performance of LoRaWAN in plain industrial scenario while the model for battery life and sensing interval evaluation is presented in Section IV for energy harvesting industrial environment. The results and discussions, covering both plain and harvesting industrial environments, are provided in Section V. Finally, the concluding remarks are presented in Section VI.

II. State of the art and essential comparison of LP-WAN Technologies

This section not only outlines the recent developments and proposals for monitoring the industrial processes but also discusses the potential of LP-WAN technologies targeting industrial use-cases [5]-[9]. Following are the few articles discussing the recent developments in this domain in terms of highlighting the significance of different LP-WAN solutions to be adopted for industrial automation and their comparison based on the range of Key Performance Indicators (KPI's) identified as critical for industry 4.0.

The first effort to highlight the significance of LP-WAN paradigm for long-term industrial scenarios was made by [9]. The authors have identified the few suitable LP-WAN candidates to fulfill the strict requirements (such as, reliability and energy efficiency) imposed by IIoT networks. The work classifies the existing industrial solutions into short-range and long-range communication technologies for IIoT and urges the latter being the future of IIoT applications for scalability, long radio coverage, roaming and, energy efficiency).

Similarly, the state of the art of LP-WAN technologies currently serving IoT applications has been reviewed by [11]. In particular, the authors focus on two famous and widely accepted LP-WAN solutions; ultra-narrow band technology by Sigfox and Semtech's Chirp Spread Spectrum (CSS) technology introduced in LoRaWAN. They held several experiments for both the solutions to evaluate their performance in terms of radio coverage and energy consumption. Concluding their remarks, the authors revealed that private networks in LoRaWAN are the future of Industry 4.0 because of their suitability towards a range of IIoT use-cases.

According to [12], the existence of LP-WAN solutions has made it possible to achieve the goals anticipated by Industry 4.0. LoRaWAN and Narrow-Band Internet of Things (NB-IoT) are identified as the key players and performance evaluation is presented arguing LoRaWAN is the best in terms of cost, battery life, and energy efficiency while NB-IoT is unbeatable with respect to Quality of Service (QoS), latency and, reliability. The authors in [12] conclude that LoRaWAN is best suited for a bulk of industrial Internet of Things (IoT) use-cases such as predictive maintenance and anomaly detection.

The QoS was one of the parameters missing in the study of LoRaWAN for industrial monitoring as mentioned in [12]. [13] proposes analytical models to investigate LoRaWAN uplink (of class A device) with respect to several parameters like latency, throughput and collision rate. The authors have conducted simulations to demonstrate the efficiency of their model and claim that their model is quite useful for the resource optimization in a cell for a preset QoS requirement.

Another insight of the LP-WAN solutions was presented by [14] which primarily highlights the notion of Low Throughput Networks (LTN). The authors evaluate the performance of different independent LP-WAN technologies flourished out before the standardization of LTN. For this purpose, they study three major technologies; LoRaWAN, Sigfox and, OnRamp. The authors conclude that the studied technologies may only be suitable for the use-cases where the constraints like jitter, delay and, throughput are relaxed despite their higher radio coverage.

The importance of industrial monitoring and control processes in terms of productivity enhancements has been emphasized in [15]. They identify a list of factors influencing performance goals (such as communication throughput, radio coverage, data security). The authors are convinced that a cellular based IoT solution is inevitable to achieve required performance level. Hence, a design and implementation of IoT network is proposed for industrial monitoring and control. The authors conclude that their proposed IoT solution performs well in terms of pre-identified parameters.

Sigfox has been considered by [16] because of its higher radio coverage, almost equivalent to that of cellular networks but against a fraction of energy consumption. The authors investigate Sigfox based heterogeneous network architecture where they propose the combination of ultra-low energy consumption star network topology suitable for short range communication with a Sigfox gateway. The authors perform several experiments with energy modeling and claim that this kind of infrastructure guarantees a large coverage areas and longer battery life (up to 4 years) of end-devices.

In addition to the aforementioned literature, some other works (e.g., [17]-[20]) also discuss the lifetime of sensor nodes through duty-cycled operation [19], [20]) on the cost of communication delays but their studies neither take into account the complex LoRa deployments nor operating costs (e.g., battery replacement and damage penalty) in industrial settings where trying to curtail the one, compliments the other type of cost. To the best of author's knowledge, this work is the premier to thoroughly investigate LoRaWAN and its carbon footprints for the industry 4.0 services in the presence of several harvesting sources to pare the reliance on battery-powered operation. Salient features of some of the major LP-WAN players, analyzed and marked suitable for industrial use-cases so far, are reviewed in Table I. The selection of a

TABLE I
COMPARISON OF LP-WAN TECHNOLOGIES STUDIED FOR INDUSTRIAL MONITORING APPLICATIONS

Parameters	LoRaWAN	Sigfox	NB-IoT
Spectrum	Unlicensed ISM	Unlicensed ISM	Licensed LTE
Business Model	Alliance	Proprietary	Proprietary
Duplex Mode	Half	Half	Half
Modulation	CSS	BPSK	OFDM
Bandwidth	125/250 kHz	100 Hz	180 kHz
Data Rates	290 bps-50 kbps	100 bps	250 kbps
Current (Sleep)	0.1 μA	1.3 μA	5 μA
Link Budget	157 dB	149 dB	164 dB
Uplink Latency	<2 s	<3 s	<10 s
Payload Size	51-243 B	8-12 B	1500-1600 B
Security	AES (128 bit)	16 bit	128-256 bit
Scalability	Medium	Low	High
Adaptive Data Rate	Yes	No	No
Interference Immunity	High	High	Low
*Current Draw @14*dBm	44 mA	49 mA	120-300 mA
Private network	Yes	Yes	Yes
Localization	Yes (TDOA)	Yes (RSSI)	No
Deployment Cost	$100-1000/gateway	$700-1200/gateway	$15000/base station
Range	2-5km urban, <15km suburban	10km urban, 50km rural	<15km urban, <35km rural

single technology is not straight forward involving different convolutions depending upon the individual use-case.

The choice of LoRaWAN for industrial monitoring and control applications (such as, anomaly detection and predictive maintenance) is justifiable because of the following reasons. First, LoRaWAN depicts the least current drawn among all counterparts in similar conditions. Second, despite being the proprietary physical layer solution itself, LoRa has an open source protocol stack as LoRaWAN that seems more open to adopt. Third, it enjoys a reasonable trade-off for throughput while operating in unlicensed ISM band. Fourth, LoRaWAN packets experience minimum uplink latency that can be of significance in industrial monitoring scenarios. Fifth, cost effectiveness is another decisive parameter that may cause standing LoRaWAN far apart from its counterparts with an added advantage of fair scalability potential within an industry. Finally, LoRaWAN has got significant attention in recent years for its rapid adaption for public network infrastructures already deployed by several network operators.

III. LORAWAN FOR INDUSTRIAL MONITORING

This section starts with shedding some light on the feasibility of LoRaWAN for industrial monitoring applications. Furthermore, it presents system model for evaluating the battery life, battery replenishment cost, and damage penalty.

LoRa has emerged as a robust physical layer propriety solution in last few years introduced by French company Cycleo, later acquired by Semtech. Thanks to its higher receiver sensitivity, LoRa can enable communications with a received signal power as low as -137 dBm operating on sub-GHz ISM band and employs wide channel bandwidth. Following these peculiarities, LoRa has been adopted as a physical layer technology by LoRaWAN protocol stack currently being promoted by *LoRa™* Alliance of over 160 members worldwide [21].

The system model envisaged in this paper considers an implementation of LoRa based monitoring devices in the industrial environment. Being a part of IIoT, the LoRa end-devices monitor several industrial parameters (such as pollution monitoring, fire detection, flow level monitoring, leakage detection, and temperature monitoring). It is pertinent to note that an average energy consumption reading for different LoRa SFs is considered assuming unidirectional (uplink) communication initiated by periodic transmitters in the lifetime evaluation. Here, the frequency of periodic transmitter (monitoring device) to sense and report an anomaly plays a significant role. Various sensing intervals are considered to investigate the average battery life against their operation on different LoRaWAN transmitting powers and Spreading Factor (SF) (ranging from 7 to 12). Furthermore, no variation in the energy consumption is evident until the application payload size of 3 $bytes$ which seems appropriate to several industrial applications for reporting an anomalous behavior.

The front-end communication in LoRaWAN network architecture takes place choosing a combination of SF, Code Rate (CR), and channel frequency. The SF can be seen as the logarithmic ratio between symbol rate R_s and chip rate R_c and can be expressed as $SF = log_2 \frac{R_c}{R_s}$. Let T_a be the time taken for submitting a packet into the sub-band for onward transmission (also named as *Time on Air* and hereafter referred as *Air Time*, T_a). Then, T_a, can be evaluated as:

$$T_a = T_{preamble} + T_{payload} \quad (1)$$

The first part of T_a is the time taken by a preamble to transmit and can be calculated as $T_{preamble} = (Length\ of\ programmed\ preamble + 4.25)\ T_{sym}$ whereas T_{sym} is the time taken to transmit only a single symbol, expressed as $T_{sym} = 2^{SF} \frac{1}{BW}$. Here, SF and BW represent the current spreading factor and bandwidth configurations being used. Similarly, $T_{payload}$ is another part of T_a, the total time needed to transmit a payload and can be viewed as $T_{payload} = No.\ of\ payload\ symbols\ T_{sym}$. Let T_{off} be the time for which the channel is unavailable for transmission (also known as Off-Time). In case the channel is unavailable, the end-node must have to wait for an interval T_{off} before it schedules the subsequent transmission. It is to note that, for the sake of simplicity, the proposed model considers retransmissions as new transmission after waiting T_{off} . As per [22], it emerges that:

$$T_{off} = T_a \left(\frac{1}{d} - 1 \right) \quad (2)$$

Following is an example of evaluating the air time and the time between subsequent packet starts in case of 0.1%, 1% and 10% duty-cyle allowance against different spreading factors in LoRaWAN as shown in Table II.

TABLE II
AIR TIME EVALUATION OF LORAWAN FOR DIFFERENT LORA CONFIGURATION SETTINGS

Spreading Factor	*Air Time - $T_a(ms)$*	Time between packet starts (s)		
		d=0.1%	*d =1%*	*d =10%*
SF7	46.336	46.34	4.63	0.46
SF8	92.672	92.67	9.27	0.93
SF9	164.864	164.86	16.49	1.65
SF10	329.728	329.73	32.97	3.30
SF11	659.456	659.46	65.95	6.59
SF12	1155.072	1155.07	115.51	11.55

The LoRaWAN configuration settings considered in the

lifetime evaluation are presented in Table III. Here, it is important to note that all the LoRa configurations settings are assumed constant throughout this evaluation. Each parameter in LoRaWAN configuration is critical and modifying this setting would consequently influence the air time. Furthermore, an application payload size of 3 bytes is considered for this evaluation as no variation in the energy consumption is recorded until this payload size which seems appropriate to several industrial applications for reporting an alert to the expert systems. For example, it can suffice the need to share the status of a range of important parameters to be monitored (such as temperature, pressure, light, acceleration, and so on) [23].

TABLE III
LORAWAN ASSUMED PARAMETERS FOR THE LIFETIME EVALUATION

LoRaWAN Parameters	Values
Application Payload Size	1-3 B
Payload size	14-16 B
Modulation Method	LoRa (based on *CSS*)
Spreading Factor (SF)	7-12
Coding Rate	4/5
Bandwidth	125 kHz
Number of Preamble Symbols	8
Frequency	865 MHz
Cyclic Redundancy Check	enabled
Explicit Header	ON
Low Data Rate Optimizer	AUTO
Transmit Power	14 dBm

As the LoRa motes are conventionally battery-powered in nature so they are supposed to adopt duty-cycled operation to reach a longer battery life. After each measurement, the monitoring nodes periodically go to sleep before their next transmission cycle. Let the sensing interval, T_{sense}, be the pause time between consecutive slots, the sleep interval, t_{sleep}, be the amount of time for which the LoRa nodes remain in sleep mode, and t_{switch} be the time taken by the nodes in switching between the active and sleep modes, then the T_{sense} can be represented as:

$$T_{sense} = t_{sleep} + 2 \cdot t_{switch}. \quad (3)$$

Sensing interval plays a crucial role for the expert systems to ensure timely decision making. Where short sensing interval helps detecting the anomaly at early stages, it also causes short battery life hence batteries are replenished frequently. Similarly, long sensing interval lets the monitoring devices maintain their operation for several years, it may incur delays in fault detection hence, production efficiency is on the stake.

A. Battery life

Here, it is important to note that the LoRa devices are assumed to be periodic transmitter where the current draw for sleep, I_{sleep}, and switching modes, I_{swap}, are 100 nA and 21.9 mA, respectively [24].

Instead, the average charge, Q, in each state (i.e., *tranmit*, *sleep*, and *switch*) can be evaluated considering the current draws in different modes of LoRa monitoring device and the time duration for which a device remains in a certain state. For example:

$$\bar{Q}_{tx} = \bar{I}_{tx} \cdot t_{tx} \quad (4)$$

where, t_{tx} is the time duration when a node is in transmit state and I_{tx} can be seen as the average current drawn in transmit mode. The total mean charge can be expressed as the summation of the products for average current draws and the time periods when a node remains in a certain state. It could be represented as:

$$\bar{Q}_{total} = \sum_{state} \bar{I}_{state} \cdot t_{state}, state \in \{tx, sleep, swap\} \quad (5)$$

Similarly, total mean energy, E_{total}, can also be the product of total average charge calculated in Eq. (5) and voltage applied (on Semtech's *SX1272*) so it can be represented as:

$$\bar{E}_{total} = \bar{Q}_{total} \cdot V_{ED} \quad (6)$$

The Semtech's monitoring devices are considered for the lifetime evaluation assuming the current draw of 44 mA for a transmit power of 14 dBm assuming the Lithium-Ion battery [24]. Here, the mean total charge and the energy consumption refers to average of six different readings for all LoRa SFs (from 7-12) with 30 repetitions each for a single mote. While testing the feasibility for a wide range of sensing intervals for LoRa motes, a fair range of sensing intervals (i.e., from 60 s to 300 s) is considered to study the impact of varying T_{sense} on the consumption reading of LoRa nodes. Moreover, following the Eq. (6), the mean energy consumption per day, E_{day}, and the mean energy consumed during a whole year can easily be evaluated. At this stage, it is possible to evaluate the average battery life, L_B, (in years) with the assumption of total battery capacity, C_B, of 1000 mAh (i.e., *11880J @ 3.3V*):

$$\bar{L}_B = \frac{C_B}{\bar{E}_{day} \cdot 365} \quad (7)$$

B. Battery replenishment cost

The replenishment cost for the batteries comprises of three sub-costs; *battery purchase*, *labor*, and the *dispose-of* cost for the replaced batteries. The first and third type of costs can be seen as fixed costs ignoring the inflation factor with time. While the second cost (i.e., labor) solely depends on the complexity level of battery replacement and the type of industry where the battery replenishment is needed. For instance, a monitoring node installed within a machinery structure is more complex to handle than the one installed on the outer surface hence, the labor cost would vary accordingly. For battery replacement cost evaluation, the assumptions drawn are presented in Table IV.

TABLE IV
ASSUMPTIONS DRAWN FOR BATTERY REPLENISHMENT COST EVALUATIONS

Cost Parameters	Assumed Values
The lifetime (in years) evaluated for Industrial monitoring devices on 14 *dBm* power output.	0.10 - 5.14
Current market value per battery (£), C_b.	3.7
The number of batteries installed per node.	1
Variable labor cost per node as per replacement complexity (£), C_r .	3.5 - 10
Cost per node for Disposing-of the batteries in T period (£), $C_{diss.}$.	0.10

The first type of cost (i.e., battery purchase cost, $C_{purchase}$) can be seen as the total capital required for purchasing the number of batteries needed in a time period as:

$$C_{purchase} = C_b \cdot N_{cycle} \quad (8)$$

Here, C_b is the cost incurred to purchase a single battery and N_{cycle} is number of replacement cycles required in a time period, T, respectively. It is significant to remark that a time

period of 20 years is assumed for the cost evaluation as it is believed to be the fair lifetime attainable through monitoring devices in energy harvesting industrial environment. Likewise, cumulative labor cost for battery installation, C_{labor}, is the variable cost that can be evaluated as:

$$C_{labor} = C_r \cdot N_{cycle} \quad (9)$$

where, C_r is the variable labor cost per node for battery replenishment based upon the complexity of installation. The dispose-of cost for batteries, $C_{diss.}$, is the cost incurred on disposing-of the replaced batteries that is not usually higher but it may still be significant in case of large-scale network deployment where thousands of nodes need replacement in a time period. $C_{diss.}$ is evaluated considering £1600 as an average dispose-of cost for every ton of wastage for the expired batteries as per the recent statistics reported by the UK Government [25]. Therefore, the total battery replacement cost, $C_{repl.}$, can be expressed as a summation of the aforementioned costs in a time period. It could be represented as:

$$C_{repl.} = \sum_{state} C_{state},\ state \in \{purchase,\ labor,\ diss.\} \quad (10)$$

C. Damage penalty

The cost incurred on damaged products manufactured on the production line due to a possible latency in anomaly detection can be referred to as the *damage penalty*. This kind of latency can also be respected as the damage interval, δT_{damage} and could be expressed as:

$$\delta T_{damage} = t_{detect} - t_{occur};\ 0 \leq \delta T_{damage} \leq \delta T_{sense} \quad (11)$$

Here, t_{detect} is the time period after which an anomaly is detected while t_{occur} is the anomaly occurrence time. Now, let P_{damage}, R_p, and C_u be the damage penalty, the rate of production at the manufacturing line, and the unit cost of production assumed for a specific unfinished product, then the damage penalty can be expressed by the following equation:

$$P_{damage} = \delta T_{damage} \times R_p \times C_u \quad (12)$$

The damage penalty is increased as a function of the damage interval with increasing value of δT_{sense}. It is important to note that different product categories (such as very expensive, expensive, medium, and cheap) are considered for the evaluation of damage penalty in different industrial scenarios with increasing unit costs, C_u (e.g., 10, 70, 150, and 500) and decreasing rate of productions, R_p (i.e., 30, 6, 3, and 1)/*min*, respectively.

IV. Energy Harvesting for Industrial Monitoring

This study considers an industrial environment with mean harvesting potential per day for three different harvesting sources to make the evaluation procedure simple. First, artificial light bulbs are considered with a potential to harvest a fair amount of energy during the working hours at 200 *lx*. Second, the harvesting potential due to change in temperature is reported to scavenge reasonable amount of energy at two different temperature gradients (i.e., 10 hour @5^{o}C and 5 hours @10^{o}C) employing TG12-2.5-01L with efficient thermoelectric effect that is based on Aluminium oxide costing only £2/kg. The cost of maintaining this thermal gradient varies depending on the type of element material being used. Third, the amount of energy harvested due to radio signals when transmitted with 3W from a distance of 5 m at 9 MHz based on Powercast P2110 harvester module which features ultralow power consumption and fairly high efficiency. The potential referred hereby is exploitable in most industrial setups and has already been utilized to feed sensors in a variety of IIoT applications [26], [27].

Surplus harvested energy from the industrial environment may be useful for achieving two significant milestones. *First*, it may serve to reduce the energy requirement of battery-powered monitoring devices by enabling them to operate on harvested energy when available. Monitoring devices only go for a battery-powered operation in the absence of harvesting energy that would eventually prolong the battery life. *Second*, as the sensing interval reciprocates damage penalty in an industrial environment, the newly harvested energy could be employed to seek the trade-off by shrinking the sensing interval up to a fair percentage without negotiating on the lifetime. This flexibility can dramatically improve the production efficiency of various product lines in industry 4.0 depending upon C_u and R_p of the manufacturing plant.

A. Battery life with energy harvesting

Let $A = \{e_1, e_2, \ldots, e_m\}$ represents the total amount of harvested energy supplied to the system through m different renewable energy sources where; $m \geq 2 \in \mathbb{N}$, then the amount of energy available in the energy buffer integrated from all m sources can be expressed as:

$$e^{buf.} = \sum_{a=1}^{m} e_a \quad (13)$$

Similarly, let $S = \{1, 2, 3, \ldots, n-1, n\} \in \mathbb{R}$ be the harvesting time divided into n different slots, then the amount of harvested energy available to the energy buffer at the end of any ith slot can be represented as:

$$e_i^{buf.} = (e_{i-1}^{buf.} - e_i^{ins.}) + e_i^{har.} \quad (14)$$

where, $e_{i-1}^{buf.}$, $e_i^{ins.}$, and $e_i^{har.}$ are the energy available in the buffer until the end of previous slot (i.e., $i-1$th), the amount of instantaneous energy consumed during current (i.e., ith) slot, and the newly harvested energy just added to the system in the ith slot, respectively. Hence, the amount of energy harvested over the period of total n slots can be represented realizing the Eq. 14 as:

$$\int_0^n E^{buf.} dn = \left[\int_0^{n-1} e^{buf.} dn - \int_{n-1}^{n} e^{ins.} dn \right] + \int_{n-1}^{n} e^{har.} dn \quad (15)$$

given that $\int_0^{n-1} e^{buf.} dn > \int_{n-1}^{n} e^{ins.} dn$ for an uninterrupted operation which implies that the amount of energy remained in the buffer during previous slots should always be greater than the energy required in the next slot. Here, replacing the value of $e^{buf.}$ from Eq. (13) in the above expression:

$$\int_0^n E^{buf.} dn = \left[\sum_{a=1}^{m} \int_0^{n-1} e^{buf.} dn - \sum_{a=1}^{m} \int_{n-1}^{n} e_a^{ins.} dn \right] + \sum_{a=1}^{m} \int_{n-1}^{n} e_a^{har.} dn \quad (16)$$

If there are n slots in a day, then the average amount of energy harvested per day, $\overline{E}_{day}^{h}$, is equal to the amount of energy added to the system over n time slots as follows:

$$\overline{E}_{day}^{h} = \int_0^n E^{buf.} dn \quad (17)$$

Now, substituting the value of $\int_0^R E^{buf.}_n dn$ from Eq. (16), we can rewrite the above equation as:

$$E_{day} = \left(\sum_{a=1}^{} \int_{0}^{n-1} e^{buf.} dn - \sum_{a=1}^{} \int_{n-1}^{n} e^{ins.}_{a} dn + \sum_{a=1}^{m} \int_{n-1}^{n} e^{char.} dn \right) \quad (18)$$

Here, the new energy requirement per day, $\overline{E}^{0}_{day}$ can be seen as a difference of previous energy demand drawn per day, $\overline{E}_{day}$, derived by the Eq. (6) and the amount of newly harvested energy per day, $\overline{E}^{h}_{day}$ that becomes the part of the system. It can be expressed as:

$$\overline{E}^{0}_{day} = \overline{E}_{day} - \overline{E}^{h}_{day} \quad (19)$$

The new battery life of LoRa monitoring nodes is reevaluated employing Eq. (7) once the new energy requirement per day, $\overline{E}^{0}_{day}$ is established. This is evaluated considering the same assumptions regarding capacity of the battery and applied voltage (*1000 mAh @ 3.3 V*) as followed in non-energy harvesting life evaluations. Here, the newly calculated lifetime would also contribute in reducing the total battery replacement cost, $C_{repl.}$, with the damage penalty being the constant.

B. Sensing interval with energy harvesting

In some industrial environments, the damage penalty causes far more harm than the frequent battery replacements. Controlling $C_{repl.}$ would not be a feasible option in those cases. To avoid/control P_{damage}, sensing interval can be shortened to more frequently update the expert systems in the presence of harvested energy while maintaining the existing battery life. This provision of interval contraction depends on the actual amount of harvested energy available at buffer in a particular instance can be equal to the relaxation in energy quota due to the availability of harvested energy at an instant. It can be seen as the ratio of the average harvested energy per day, $\overline{E}^{h}_{day}$, to the energy demand per day, $\overline{E}_{day}$. Thus, the contracted interval in case of energy harvesting availability, δT^{0}_{sense}, could be represented as:

$$\delta T^{0}_{sense} = \delta T_{sense} - \left(\frac{\overline{E}^{h}_{day}}{\overline{E}_{day}} \right) \quad (20)$$

This contracted sensing interval would enable the fair reduction of the damage penalty, P_{damage}, setting the battery replacement cost as a constant.

V. Results and Discussion

This section spans the results of LoRaWAN evaluation following the proposed model (elaborated in Sections III and IV) along with a detailed discussion on these results. It can be divided into two sub-sections; i) standard LoRaWAN evaluation for industrial monitoring and ii) LoRaWAN in industrial monitoring with energy harvesting capabilities.

A. LoRaWAN evaluation in industrial monitoring scenarios

1) Energy consumption : Energy consumption can be seen as the foremost LoRaWAN parameter that serves to evaluate the battery life in the industrial environment. Figure 1 presents the average energy consumption of LoRa monitoring node per day against a range of fair sensing Intervals. The average energy consumption is the average value of all the energy consumptions reported while operating on different LoRaWAN spreading factors. The maximum value of energy consumption (almost 85 J a day) is reported when the node senses every minute. It is obvious to note that the average consumption goes on decreasing as sensing interval is increased. For example, the average value of energy consumption per day is at the minimum when LoRa monitoring nodes sense and report for an anomaly every five minutes.

2) Battery life with different transmitting powers: After evaluating the energy consumption, the average battery life can also be calculated as reported in Figure 2. As LoRa monitoring devices are capable of transmitting with different output powers, the results are taken with four different power configurations ranging from 13 *dBm* to 20 *dBm*. The battery life is significantly increased between 1 *min* and 5 *min* sensing intervals. The maximum battery life (of approximately 8 years) can be observed in case of 13 *dBm* as the current draw in this configuration is minimum (28 *mA*) as compared to configuration of 20 *dBm* when the monitoring nodes undergo maximum current draw (125 mA) yielding less than 2 years of battery life [24].

Here, 14 *dBm* is the maximum transmission power allowed for an emitter in 1% duty cycle sub-band under European legislations for transmission power restrictions. Figure 3 zooms into the 14 *dBm* power configuration setting where the monitoring nodes successfully achieve a lifetime of 5 years when they wake back every 5 *min* to measure and transmit. The monitoring nodes with sensing interval of less than 1 *min* are not able to last for even an year. Here, it is interesting to note that the delay of every minute after the first minute in the sensing interval yields almost one-year increment in the overall battery life of monitoring node in this case.

3) Sensing intervals compatible with LoRaWAN: The number of messages per day in LoRaWAN depends on the two different factors. First, the choice of spreading factor for communication as every *SF* in LoRaWAN incurs different air time. Second, duty-cycle of a particular sub-band available for communication as there may be multiple sub-bands at each transmission with different duty-cycle allowance (e.g., 0.1%, 1%, or 10%). Figure 4 gives an overview of the maximum number of messages that can be transmitted by a monitoring node deployed across the production line when different active and sleep periods are selected. The higher the duty-cycle allocation, the higher the number of messages. The number of messages reduce significantly moving along the SFs up to only a few messages per day in case of SF12 and 0.1% duty-cycle.

Figure 5 shows how different sensing intervals are supported by different *SFs* in LoRaWAN in terms of number of messages compatibility. For example, only SF7 can support the maximum number of messages with 5 s sensing interval and monitoring nodes cannot employ other spreading factors available in LoRaWAN to practically transmit this number of messages. It is obvious that LoRa monitoring nodes only support the sensing intervals above 60 *s* to avoid violating of duty-cycle compliance. It implies, a fair range for sensing interval in LoRaWAN can only be in terms of minutes (i.e., from 1 *min* to 5 *min*). Therefore, rest of the results assume this range of sensing intervals.

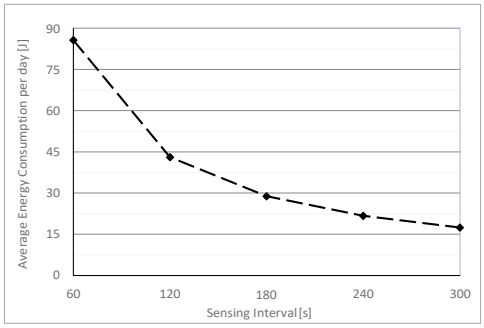


Fig. 1. Average energy consumption per day against sensing intervals

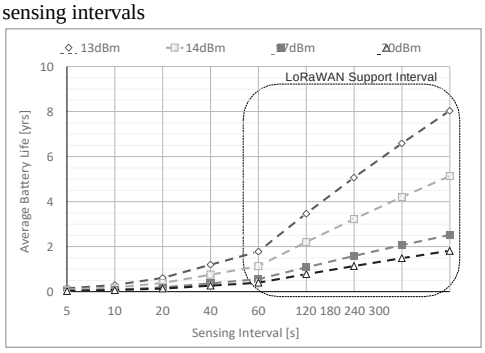


Fig. 2. Average battery life of monitoring device considering different transmitting powers in LoRaWAN

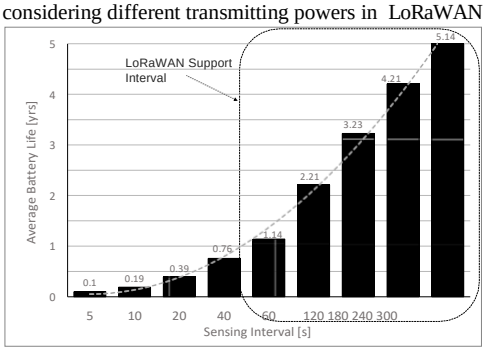


Fig. 3. Average battery life achievable assuming 14 *dBm* transmission power

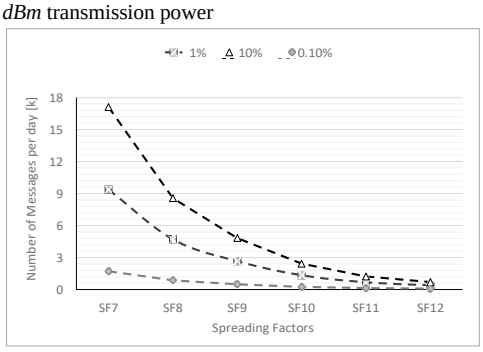


Fig. 4. Maximum number of messages acheivable per day with different LoRa settings considering regional duty cycle restrictions

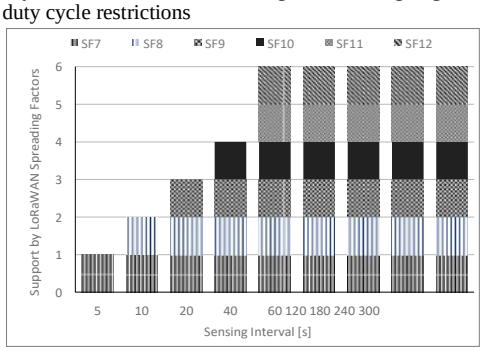


Fig. 5. LoRaWAN support for sensing intervals in case of 1% duty cycle restriction by EU regulations

4) Statistics for battery replacement cost: The higher management in a smart industry always finds it difficult replacing the batteries of monitoring nodes for two reasons; (i) it incurs a lot of industrial resources in terms of cost and time, (ii) the entire production process needs to be in non-operational state that results in huge financial losses and deteriorates production efficiency. Figure 6 presents cumulative battery replacement cost as a function of variation in the installation labor cost when it is considered between £3.5 to £10 per replacement as per the complexity of the spot. These costs are anticipated for a fair range of sensing intervals identified in Figure 5. It is obvious that cumulative battery replacement cost keeps increasing when shortening the sensing interval as extra number of replacement cycles are required when the LoRa devices wake back frequently (such as, in 1 *min* interval). Likewise, variation in the replacement cost does not affect much for the sensing intervals above 2 *min* and is reported just over £100.

5) Statistics for damage penalty: The damage penalty can be seen as the second type of cost but higher enough to be paid significant attention by the administration of a smart industry. The longer the sensing interval, the longer the damage interval it may cause. The best case can be the lower bound of sensing interval so that to avoid any delays in detecting the anomalous situation. Similarly, the worst case may be the longest sensing interval when the anomaly was occurred just after the previous cycle and the smart system would be able to detect this anomaly in the next cycle at the earliest after waiting for the whole sensing interval (e.g., δ_{sense} = 5 *min*).

Figure 7 compares four different product lines from industry 4.0 with different unit costs and production rates given in Section III. Although there is not a noticeable difference between the damage penalty of all four cases on lower part of sensing interval, but as we move on to higher sensing interval, the difference appears to be significant. The product with minimum unit cost and higher production rate seems to be the most ideal case when the penalty does not go beyond £1500 even with the longest sensing interval (i.e., 5 *min*). The damage penalty may go up to £2500 in case of maximum unit cost and lowest production rate following the same sensing interval.

6) The overall cost in non-energy harvesting scenarios: The overall cost includes both types of contradictory costs evaluated previously; battery replacement cost and damage penalty. Figure 8 throws light on an overall picture depicting both types of cost to estimate a clear contribution of each type of cost. It is significant to note that the results in the all four product categories witnessed the same trend (i.e., linear increase in cost) hence, due to the space limitations, the only instance (i.e, C_u = £10 and R_p = 30/min) was opted to demonstrate the trend as in Figure 8. To present an example, the damage penalty is recorded when the unit cost of production is £10 and the rate of production reaches 30 *products per minute*. Initially, the proportion of battery replacement cost is 44% in comparison to overall cost that goes down to 3% of the overall cost when the LoRa monitoring nodes reach *5 min* of sensing interval. On the other hand, damage penalty is doubled over every minute of sensing

interval starting from £300 (when sensing interval is *1 min*) to £1500 in case of $6T_{sense}$ = *5 min*.

B. LoRaWAN in industrial monitoring scenarios with energy harvesting capabilities

Industrial potential for renewable energy comes into play in two different ways. *First*, due to the presence of harvested energy from the industrial environment, LoRa monitoring nodes can be fed by newly harvested energy minimizing the battery powered operation. *Second*, thanks to the energy scavenging capabilities present in industrial environment, sensing interval appears to be flexible and can be contracted as per the relaxation in energy quota. This section highlights the benefits of exploiting the harvesting potential in terms of extended battery life and flexible sensing interval and provides insight of how LoRaWAN performs far better in the presence of harvested energy as compared to the evaluations drawn in the previous sub-section.

1) Prolonging the battery life: Extended battery life is the first milestone that can be achieved taking energy harvesting into account within industrial environment. The damage penalty and the battery replacement cost both are significant but exhibiting inverse relationship. It implies that if we try to control one, the other may go up in plain industrial environment. While the potential for harvesting energy within an industry 4.0 can turn them around.

a) Lifetime of LoRa motes in harvesting industrial environment: In harvesting environment, the extra harvested energy is able to further prolong the lifetime of monitoring nodes several times as compared with plain industrial settings when moving along the sensing intervals, as shown in Figure 9. The updated lifetime would significantly contribute towards reducing the $C_{repl.}$, as shown in Figure 10. It can be observed that even in case of shortest sensing interval of a minute, the battery life can be extended many folds when utilizing harvested energy without changing the sensing interval.

b) Battery replacement cost in harvesting industrial environment: The battery replacement cost can also be trimmed by prolonging the lifetime of moni oring nodes in a harvesting industrial environment. Figure 10 clearly argues about chopping $C_{repl.}$ as low as just over £13 when $6T_{sense}$ approaches over 3 *min* in comparison to counterpart where it jumps over £80. Moreover, $C_{repl.}$ keeps rising as the sensing interval is reduced. As extra battery replacement cycles are required if the LoRa motes wake up back and forth (such as, in 1 *min* interval). Whereas $C_{repl.}$ maximally reaches £50 in energy harvesting scenario even when the $6T_{sense}$ = 1 *min* in comparison with non-energy harvesting scenario where $C_{repl.}$ is reported over £230 for the same interval.

2) Contracting the sensing interval:

a) Interval contraction rate: As mentioned in section V-B, the flexibility in the sensing interval can be achieved as an added advantage in addition to prolonging the lifetime of LoRa devices. Figure 11 demonstrates the interval flexibility rate (in percentage) at which $6T_{sense}$ could be reduced in case of renewable energy. Here, it is worth mentioning that the rate of interval contraction ranges from 14% to 70% moving from 1 *min* to 5 *min* sensing interval based on the amount of newly

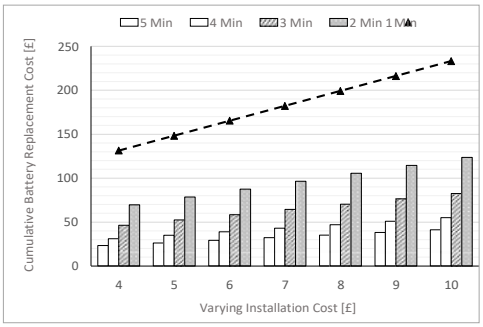


Fig. 6. Cumulative battery replacement cost against variation with respect to complexity

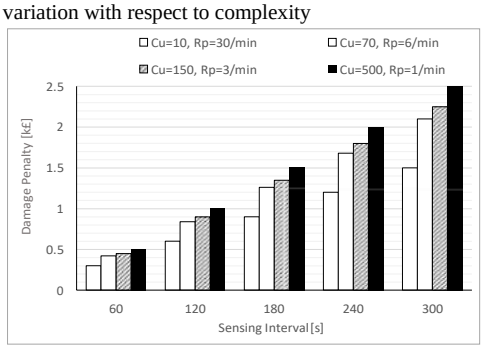


Fig. 7. Damage penalty with respect to various sensing intervals

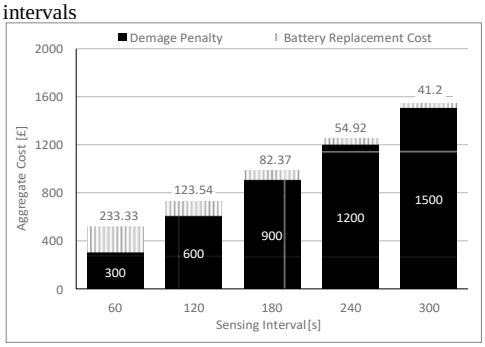


Fig. 8. Aggregate cost summarizing damage penalty and battery replacement cost when C_u = £10, R_p = 30/*min*

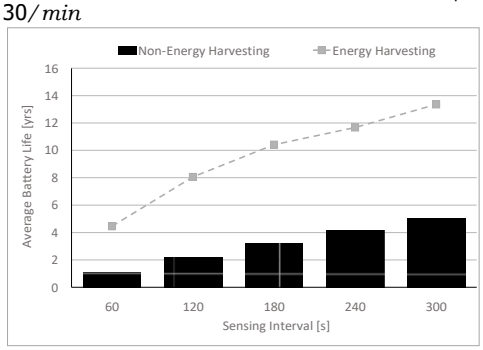


Fig. 9. Average battery lifetime comparison of plain and energy harvesting industrial scenarios employing LoRaWAN

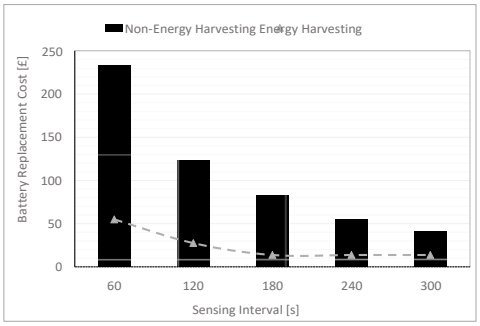


Fig. 10. Comparison of battery replacement cost when exploiting energy harvesting sources in industrial envi-

ronment

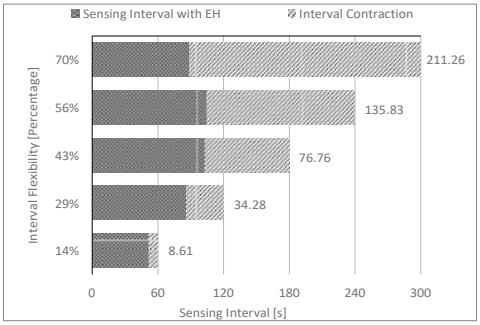


Fig. 11. Sensing interval flexibility and the rate of interval contraction when exploiting energy harvesting sources in industrial environment

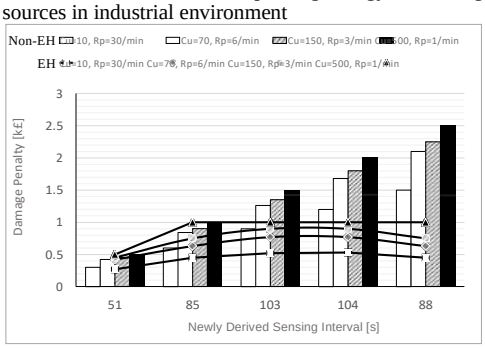


Fig. 12. Comparison of damage penalty against newly derived sensing intervals when exploiting energy harvesting sources in industry 4.0

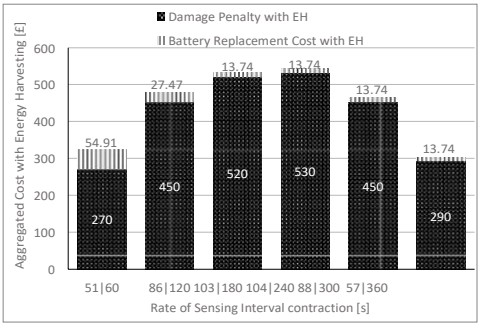


Fig. 13. Aggregate cost within energy harvesting environment against rate of sensing interval contraction

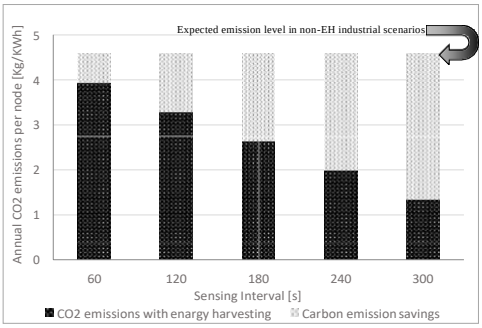
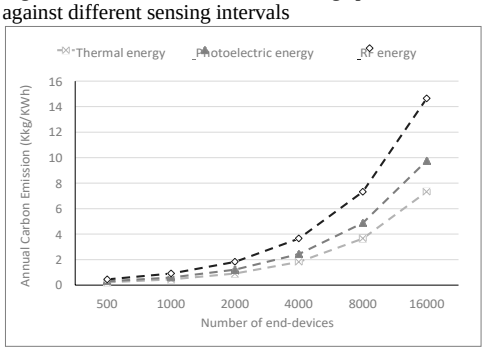


Fig. 14. Annual carbon emission savings per node against different sensing intervals



harvested energy available. The greater the sensing interval, the higher the relaxation in the energy quota and consequently, the higher the percentage of interval flexibility. It implies, a 5 *min* preset sensing interval for an IIoT application can be reduced to as short as 1.5 *min* whenever needed to reduce the long damage interval, δT_{damage}, and to diminish higher damage penalty, P_{damage}.

b) Damage penalty in harvesting industrial environment: It is even critical for the smart industries manufacturing costly products (i.e, higher C_u) where each damaged product causes far huge penalty as compared to $C_{repl.}$. Therefore, instead of attaining the longer battery lifetime in the Section V-B1, we can utilize newly harvested energy to derive a shorter sensing interval, δT_{sense} as permissible by the quota of harvested energy available at hand. Thanks to the interval contraction via harvested energy, it is possible to restrict the damage penalty (see Figure 12) to an upper bound of £1040 above the interval of $85s$ ($120s$ previously i.e., up to 29% shorter), even when considering the most expensive product category. The damage penalty can be confined as low as £520 in the smart industries with lower C_u.

c) Aggregate costs in harvesting industrial environment: Figure 13 exhibits the overall cost picture where the aggregate of both costs (i.e., P_{damage} and $C_{repl.}$) is compared with non-energy harvesting scenario in Figure 8. The impact of interval contraction on both costs clearly argues about the non-linear increase in P_{damage} and $C_{repl.}$ moving along higher intervals. With the increase in the contraction rate in harvesting environment, the aggregate cost tends to go significantly down along the higher sensing intervals. The cost reported by most right bar in Figure 13 on $\delta T_{sense} = 360s$ are even lower than the value reported on $\delta T_{sense} = 60s$ which favors the selection of greater interval.

3) Carbon footprint analysis for LoRa devices: Following the ascent in the global warming curve, serious efforts have been put in place by various segments of the society to de-carbonize the environment, fairly reducing the carbon footprints. The smart industries are also well on their way to green industrial revolution by taking several measures to reduce carbon footprints from different industrial processes. The employment of renewable energy sources not only offers industrial cost savings but also contributes to fairly drop the extent of carbon footprint caused by the conventional power generation.

Despite the green energy solutions, it is important to note that each kind of renewable energy source is associated with a certain amount of carbon per kWh of generation. By distributing these carbon emissions on the lifetime of the system, we can consider an amount of carbon associated with each type of renewable energy source as $15g/kWh$, $20g/kWh$, and $30g/kWh$ for thermoelectric, photoelectric, and RF energy respectively [28], [29] as compared to the CO_2 emission of fully battery powered monitoring devices as $150g/kWh$ [30]. Let $CO_2^{batt.}$, CO_2^{TE}, CO_2^{PE}, and CO_2^{RF} are the carbon emissions associated with fully battery-powered, thermoelectric, photoelectric, and RF energy respectively and $E_{year} = V\ I\ 24\ 365$, then by multiplying the carbon footprint associated with a renewable energy source to E_{year} yields an

Fig. 15. Carbon footprint analysis in presence of energy harvesting technologies in industrial environment

annual carbon emission of corresponding energy source.

Similarly, annual carbon emission savings per LoRa node can also be evaluated by subtracting the annual CO_2 emission in the presence of energy harvesting sources from the expected carbon emission in fully battery powered solution (i.e., $4.58 Kg/kWh$). It can be expressed as:

$$CO_2^{savings} = E_{year} \cdot (CO_{2batt.}) - (CO_{2TE} + CO_{2PE} + CO_{2RF}) \quad (21)$$

Figure 14 presents the annual CO_2 emission savings per LoRa node against the sensing interval. The longer the sensing interval of LoRa monitoring nodes, the greater the savings on carbon emissions. It is significant to note that a saving up to $3.22 kg/kWh$ per LoRa node is possible annually on the sensing interval of 5 min that accounts for tons of annual carbon emission savings for a large scale network. Figure 15 demonstrates the annual emission savings in a large scale LoRa network as a function of the number of end-devices. It can be concluded that even a medium scale LoRa network deployment with energy harvesting devices may save several tons of carbon emissions annually which is quite encouraging for the industrial administrations to consider energy harvesting LoRa deployments to actually realize the dream of green industrial revolution.

To summarize, the work yields the following important developments. First, P_{damage} is always higher than $C_{repl.}$ for greater intervals and the curves belonging to these costs meet across the sensing interval of 1 min. Second, $C_{repl.}$ goes down significantly because of the longer lifetime achieved through harvested energy without having any impact on δT_{sense}. Third, the surplus harvested energy also induces the flexibility for the interval contraction towards generating recent alerts. Fourth, the proper exploitation of harvested energy in an industrial setup cuts down both types of costs (i.e., P_{damage} and $C_{repl.}$) to end up with the reduced aggregate cost in caparison with non-energy harvesting industrial environment. Fifth, the aggregate cost does not depict a linear increase in harvested environment and starts declining when $\delta T_{sense} = 240s$. It goes down to as minimum as £300, especially when $\delta T_{sense} = 360s$, even lower than the aggregate cost recorded on $\delta T_{sense} = 60s$.

VI. Conclusion and Future Activities

The work first presented a model to evaluate the energy consumption, estimating the battery life of LoRaWAN monitoring devices in an industrial environment. It then exploited several renewable energy resources available in a smart industry to highlight the impact of harvesting potential on the battery replacement cost and damage penalty. Furthermore, it studies the interesting relationship between the aforementioned costs in industry 4.0 to understand how these costs reciprocate each other in a smart factory where the damage penalty can, sometimes, be far huge compared to battery replacement cost. Moreover, the results first evaluate several critical parameters of LoRaWAN in a plain industrial environment and then a comprehensive comparison is provided with energy harvesting industrial environment. The future work would consider applying the similar model on 802.11ah, 802.11ax and 802.11be (EHT). Moreover, the work can also be extended towards formulating an optimization problem where maximizing the lifetime is an objective function with both the costs (i.e., battery replacement costs and damage penalty) as constraints.

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