Towards Factory Schedule based Adaptation for Reliable Networking in Industrial IoT

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***Abstract*—In this paper, a novel paradigm of adapting wireless communications based on the factory schedules in an indoor factory floor is explored. Since the fourth industrial revolution (4IR) strengthens the industries with a wide range of advanced applications such as digital twin and predictive maintenance, a large number of devices and systems are deployed densely near machines in a factory floor. Such new devices and systems, along with the existing systems, are networked by the Industrial Internet of Things (IIoT) wirelessly for their functioning. Devices closer to machines have a greater probability of interference from the operation of the machine. Since the operation of machines in a factory are often scheduled, their impact on wireless communication can be learnt and predicted. The first step towards it is, to estimate the effect of various processes in a factory schedule on wireless communication. This research empirically investigates the extent and nature of the impact of factory schedules and presents its findings. The obtained results indicate that the machines influence the packet reception rate (16% on an average), positively for certain nodes while negatively for others. Furthermore, based on these findings, this paper categorizes the factory schedules into two broad categories ('Macro' and 'Micro' processes) and discusses the challenges in developing a mechanism to detect and classify them. The interference detection and identification can have applications such as scheduling delay-tolerant traffic and adjusting power levels while transmitting a packet apart from increasing reliability of IIoT.**

***Index Terms*—Industrial IoT, Networking, Factories of the Future, Interference Aware Transmission, Fourth Industrial Revolution**

I. Introduction

Manufacturing industries are at the dawn of the fourth industrial revolution (4IR). Following the previous three revolutions, 4IR will increase the level of automation by adding a cognitive power to augment decision making [9]; resulting in the development of a vision called Factories of the Future (FotF) into reality. The major technological enabler for FotF is Internet of Things (IoT) attributed as Industrial IoT (IIoT). IIoT facilitates FotF with new applications such as Digital Twin (DT) and Predictive Maintenance (PdM). A fully functional IIoT system can have thousands of devices (sensors, actuators, computational devices, etc.) and some of them require mobility support. Therefore the wireless network for IIoT should be adaptive to support scalability and mobility while being reliable at the same time [10], [11].

Achieving a reliable wireless network is intricate owing to the harsh wireless conditions in an industry. Major reasons for this include interference from typical operation of machines, multiple radio access technologies operating in the same frequency band and metallic infrastructures [12]. Since most of the currently available solutions for industrial wireless connectivity such as WirelessHART, ISA100.11a, WISA, WIA-PA, iWLAN, Bluetooth Low Energy (BLE) and IEEE 802.11-based networks operate on the same frequency band - 2.4GHz, each of them use diverse co-existence techniques to weaken the effect of interference from co-located similar/dissimilar networks [13]. These techniques do not guarantee quality of service [8]. Therefore, the international standard, IEC 62657(2) [14] recommends usage of Interference Aware Transmission (IAT) for industrial wireless networks.

The initial step towards IAT is to detect the sources of interference and identify them (referred to as IDI) [8]. The focus of IDI based schemes in available literature is on identifying interference from other wireless technologies operating in the same frequency band (usually the 2.4GHz ISM band) [2], [6] and not on the interference caused by machines operating in the factory floor. However, 4IR applications like DT and PdM require extensive multi-modal sensing as well as actuation, predominantly within the vicinity of machines present on the factory floor. Therefore, the impact of machine operation on wireless communication of sensors deployed for DT and PdM become more prominent and important to mitigate.

Researchers have found that the interference characteristics largely depend on the topology of the factory floor [12]; in particular the presence and operation of heavy rotating machines [15]–[17]. Since the processes in a factory floor are scheduled to happen in a particular sequence and the sequence repeats in fixed intervals, the schedules can be learnt and later used to adapt communications. Therefore, an intelligent adaptation strategy for achieving reliable networking in FotF could be, to detect and identify the interference caused by schedules (operation of machines) and adapt the communications accordingly. To the best of our knowledge, there is not any literature available that focuses on developing an IDI mechanism which classifies the machine operation. This paper aims to initiate this new research direction by performing the initial steps required in building such a system. The major

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TABLE I
A COMPARISON OF PROMINENT IDI WORKS IN IOT AND IIOT CONTEXTS.

Reference	Data Used	Methodology	Industrial	Interference Source Classified
[1], [2]	Bit error pattern	Threshold-based algorithm	✓	IEEE 802.11b/g, Multi-Path Fading and Attenuation
[3]	Spectral features of received signal	Spectral-features-based algorithm	✗	IEEE 802.11b and Microwave Oven
[4]	Spectral features of received signal (dual-radio)	Spectral-features-based algorithm	✗	Multiple 802.11 networks
[5]	Temporal features of received signal	Temporal-features-based algorithm	✗	IEEE 802.11 or Bluetooth or Microwave Oven
[6]	Spectral features of received signal	Supervised Machine Learning	✓	IEEE 802.11 and Microwave Oven
[7]	Temporal features of received signal	Unsupervised Machine Learning	✗	Multiple 802.11, Bluetooth and Microwave Oven
[8]	Spectral features of received signal	Supervised Machine Learning	✗	IEEE 802.11b/g/n, 802.15.4, 802.15.1, and BLE

contributions of the paper are:

1) Experimentally estimating the effects of factory schedule (focusing on machine operation) on devices communicating within a factory-floor-like environment;
2) Identifying and categorizing the challenges involved in developing a mechanism to detect and classify schedules in a factory-like environment; and
3) Proposing approaches to overcome identified challenges in developing an IDI mechanism.

Based on our findings presented in this paper, we plan to develop an IDI algorithm as a future work.

The rest of the article is organized as follows, Section II presents a brief overview of related IDI works available in literature. The experiment set-up is elaborated in Section III. The findings of the experiment (influence of machine operation) are presented along with their insights in Section IV. Based on the findings, in Section V, the challenges in developing an IDI system that classifies machine operation state is presented along with possible approaches to overcome the identified challenges. Lastly, Section VI presents the conclusions of the research performed along with potential future works.

II. RELATED WORKS

As mentioned in the previous section, IDI mechanisms empower devices operating in unlicensed frequency band to identify/classify sources of interference for better co-existence. The available literature on IDI can be divided into two broad categories based on the data used for IDI. They are: 1) Bit Error Pattern (BEP) based [1], [2], [18]; and 2) Received Signal Features based [3]–[8].

Barac et al. [1] and Sisinni et al. [2] proposed BEP based hard-coded-threshold algorithms to identify the source of interference as either IEEE 802.11b/g networks or multi-path fading and attenuation with varying accuracy. Since Pereira et al. [16] and Nabetani et al. [15] observed machines affecting the features of received signal during their experiments to characterize indoor industrial environment, it is plausible to use features from received signals to detect the interference caused by presence and/or operation of machine.

Using the features of the received signal to perform IDI has been widely researched in the context of IoT and not so much in that of IIoT. Although currently there are not any IDI mechanisms detecting the interference caused by machines, it is interesting to briefly discuss about existing approaches in literature. Chowdhury et al. measured spectral characteristics of IEEE 802.11 networks and an operational microwave oven to obtain a reference spectrum shape [3]. Later the reference shape was used to classify interference during network operation. Zacharias et al. proposed a different approach towards IDI based on the temporal variations in received signal. Using temporal features over spectral features removes the necessity to demodulate received signal for IDI processing [5]. However, the drawback of Chowdhury et al.'s and Zacharias et al.'s approach is that the approach does not identify the presence of more than one co-located source of interference [3], [5]. Ansari et al. partially overcame this disadvantage by proposing a spectral-features-based algorithm which was capable of identifying multiple co-located 802.11 networks [4].

Iyer at al. proposed an unsupervised machine learning (ML) approach titled 'SpeckSense' to tackle the problem of identifying multiple sources of interference operating simultaneously [7]. SpeckSense's interference detection component clustered RSSI samples. These clusters were then passed on to the interference identification component which observed periodicity in order to classify the presence of multiple sources of interference. SpeckSense was shown to detect and classify multiple IEEE 802.11, Bluetooth networks and operation of microwave oven.

Recently, Grimaldi et al. utilized a combination of spectral characteristics and RSSI envelope to detect presence of previously undetected/unclassified wireless networks such as IEEE 802.15.1 [8]. This work was performed and evaluated in an IoT environment. In another work by Grimaldi et al., they had proposed an ML based IDI for industrial applications [6]. Interestingly, that is one of the very few works available for IDI in an industrial setting. The authors successfully identified presence of IEEE 802.11 networks in industrial environment. In addition, they also identified the presence of a microwave oven although it is not a common situation to have a microwave oven in a factory floor.

Table I compares the prominent related works based on the data used to formulate their methodology. The Table I also presents the sources detected and identified by IDI mechanisms in related works. Furthermore, it also mentions if they were designed and evaluated in an industrial setting.

III. Experimental Setup and Data Acquisition

The experiment was performed in a metals workshop in the University of Twente, The Netherlands. The workshop was accessible to students and researchers to perform experiments during working hours on working days. During non-working hours (and days), the operators are restricted from accessing the workshop. The workshop had heavy machines which, during operation, have high-speed rotating components. The layout of the workshop is presented in Figure 1. The top part of the figure contains box plots of RSSI for each node during the operation of various machines. This plot is presented alongside the layout for readers' ease but is explained in Section IV. The workshop had nine units of metallic lathe machine, each with dimensions of 1.5m x 0.5m. They are used in shaping metallic work-piece. Machines can only be operated from a fixed position. These positions are illustrated with images of operators adjacent to the machines in Figure 1. The environment also had a wooden table upon which the transmitter node (labelled as 'T' in Figure 1) was mounted. Let M represent the set of machines and m_i represent an individual machine; then $M = \{m_i | i \in \{0, 1, 2, 3, 4, 5, 6, 7, 8\}$. Machines m_2, m_4 and m_7 are separated from machines m_3, m_5 and m_8 by a distance of 1.25 meters. The workshop is accessed through a door located behind machine m_0. It is important to note that not all machines were operational throughout the experiment period. The operators (students or researchers) work with a machine of their preference. However, during the experiment period, operators were encouraged to use one of m_0, m_1, m_2, m_3, m_4 and m_5.

The transmitter node was configured to operate in injection mode of 802.11n protocol at 5GHz frequency band. In the injection mode, the transmitter broadcasts packets at the specified transmission rate, packet size and channel. In principle, all receivers listening on that channel shall receive the broadcasted packets. The injection mode was used in order to observe the effects of machine operations on different receivers simultaneously. No other external influences such as WiFi operating in 5GHz frequency band were found in the vicinity of the workshop.

In order to observe the effect of machine operation, three receivers were strategically placed. The first receiver node (N1 in Figure 1) was placed in such a way that machine was the only thing between the transmitter and receiver nodes (the pathway between Machine m_1 and the wooden table was restricted for usage). The second receiver node (N2 in Figure 1) was placed just across the transmitter node thereby acting as a line-of-sight node. In principle, N2 will be able to pick-up the effects of people crossing the pathway. The third receiver node (N3 in Figure 1) was placed behind a machine which was across the pathway. In principle, results from this node would reflect the effects of a pathway along with operation of

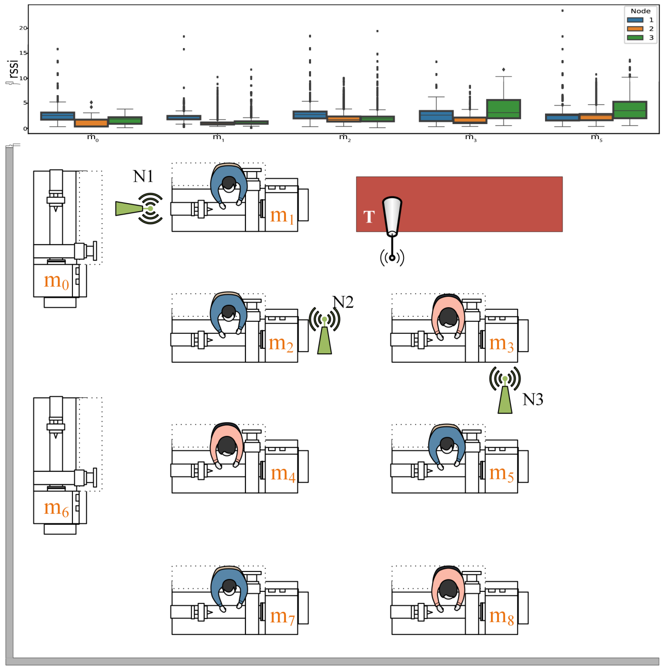

Fig. 1. *Top:* Box plot of normalized RSSI for each node when different machines were operational. *Bottom:* Experiment setup in a metal workshop

machine. Approximately, N1 and N3 were 2 and 2.75 meters away from the transmitter, while N2 was just 0.75 meter away from the transmitter. The node orientation and height were constant throughout the period of experiment. All the receiver nodes were placed very close to the machines because 4IR applications such as DT and PdM require sensing on the surface of operating machines [19].

The experiments were carried out for six continuous days. Let D represent the set of days and d_i represent an individual day; then $D = \{d_i | i \in \{1, 2, 3, 4, 5, 6\}$. Among the six days of experiment, four were working days represented as $D_W = \{d_i | i \in \{1, 4, 5, 6\}\}$ and two were non-working days represented as $D'_W = \{d_i | i \in \{2, 3\}\}$. On d_1 and d_6 the measurements were only conducted half day (second half of d_1 and first half of d_6).

A machine can be in one of the following states: 'Off', 'Idle' or 'Running' represented as $S = \{s_i | i \in \{0, 1, 2\}\}$ respectively. During the 'Off' state (s_0), the machine is completely switched off. During this state there may or may not be operators present adjacent to the machine. In the 'Idle' state (s_1), the machine is in stand-by i.e., the exhaust fan is operational while in the 'Running' state (s_2), the head spindle - principle rotating component, is operational. Operators are allowed to leave the machine in 'Idle' state (s_1) but not in 'Running' state (s_2). During the experiment, the state of the machine along with the presence of operator was noted. The raw data is made available in [20].

IV. Exploratory Data Analysis and Results

In order to single out the effects of machine operation in a factory-floor like environment, the collected data was split

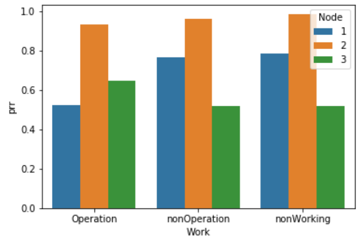

Fig. 2. Packet Reception Rate of each node in different classes

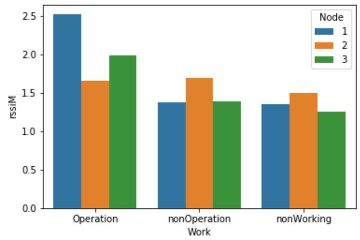

Fig. 3. Mean of normalized RSSI per node in different classes

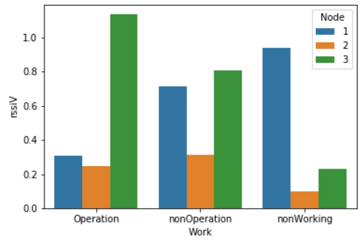

Fig. 4. Variance of normalized RSSI per node in different classes

into three classes based on the hours of operation.

C_1 - *'Operation'*: In general, when a machine operates in s_1 or s_2, an activity is said to occur and data collected during those hours constitute class C_1, Investigating data in C_1, provides insights into the effect of machine operation on packet reception.

C_2 - *'nonOperationWork'*: This class constitutes the data collected during the working hours of the workshop when none of the machines were in operation (s_0). Data in C_2 aid in reasoning the differences caused by changes in the environment around the experimental area (working vs non-working day).

C_3 - *'nonWorking'*: This class constitutes the data collected during non-working hours of the workshop. Investigating data in C_3 provides insights into environment such as the *presence* (not operation) of machines. Therefore C_3 serves as the baseline.

The packet reception rate (PRR) per receiver node per class is investigated and the results are presented in Figure 2. Regardless of the class, line of sight node N2 receives the most number of packets. The difference in PRR between classes C_2 and C_3 is marginal, suggesting that the PRR remains unaffected by external influences caused during working hours. In class C_1, although all nodes are placed within the same environment and are subjected to the same factors (machine operation), the PRR of nodes vary significantly from other classes namely C_2 and C_3. These variations are due to the operation of machines but the variations are not homogeneous. Some nodes are positively influenced while others are negatively influenced by operation of machines. Nodes N1 and N2 are negatively influenced by the operation of machines. The extent of the influence varies between them. Node N1's PRR reduces by 27.5% while that of node N2 only drops by 6.6%. The reason behind this phenomena is that, N2 is the closest to the transmitter as well as in line of sight of the transmitter. Contrary to nodes N1 and N2, node N3 is positively influenced by operation of machines; its PRR increases by about 15% in Class C_1.

The other features (apart from PRR) analyzed are mean and variance of normalized ('standard score') RSSI in each node. These features were chosen in our research because the references [15], [16] observed disturbances in RSSI during the operation of machines. These disturbances could potentially

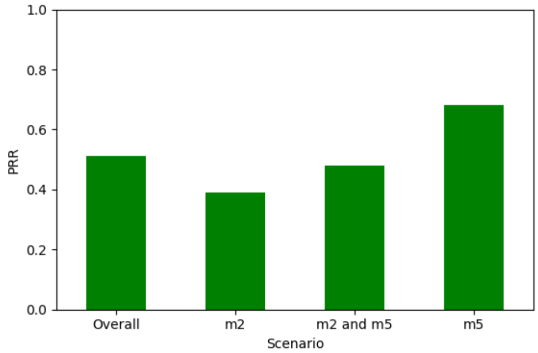

Fig. 5. Packet Reception Ratio of node N3 under different scenarios

have characteristic information about the machine operation, hence they were examined in this research. A comparison of the three examined parameters is presented in Figures 2, 3 and 4. The mean of RSSI has the same distribution for classes C_2 and C_3. So, the external influences during working hours do not have a significant effect on the RSSI on an average however, the effect is reflected in variance. The high variance in RSSI of node N1 during 'nonWorking' hours (C_3) can be attributed to its placement close to the workshop door. Since N3 was the node farthest away from the transmitter, the machine operation resulted in notable fluctuations in RSSI. This effect can also be noted in box plot of Figure 1 wherein the inter-quartile distance of N3 is larger when machines m_3 or m_5 operate than when other machines operate.

Upon further investigation of N3, it was found that different machines affect N3's PRR differently. When machine m_5 is operating in state s_2, the PRR of node N3 is 18% greater than the overall PRR experienced by N3. However, when machine m_2 is operating in state s_2, the PRR of node N3 is 11% lesser than the overall PRR experienced by N3. Hence, it is evident that operation of machines is not always detrimental to packet reception. When both machines m_2 and m_5 were in operation the PRR of node N3 is closer neither as high as when m_5 was in operation or as low as when m_2 was in operation. These observations are presented in Figure 5 along with the overall average PRR observed in node N3 in class C_1.

From our experiments, it is evident that the operation of machines have a notable effect, either positive or negative, on packet reception rate. This phenomena becomes even more important to study in the context of 4IR since it involves placing devices requiring wireless connectivity on the machine within a factory floor. Variations in RSSI are marginal and hence are not conclusive enough. Further investigations into RSSI based IDI is required.

V. Challenges in IDI and its Inferences

Factories, to a large extent, have fixed schedule of operation. Processes in the factory schedule repeat over varying timescales. Some processes in the factory schedule repeat over hours (quality check of product produced), while others repeat over milliseconds (rotating component of a machine). This results in diverse challenges in developing an IDI mechanism as well as presents diverse applications for utilizing the identified factory schedule. Hence, we define two classes of processes in a factory schedule. They are:

1) Macro Processes; and
2) Micro Processes.

A. Macro Processes

Processes of a factory such as change in operation shifts, change in properties of product produced, etc. have longer timescale of repetition, usually in the order of hours and days. Such processes in a factory schedule constitute 'Macro processes'. In the experiment conducted, the classes C_1, C_2 and C_3 are macro processes.

Challenges & Inference: In the experiment conducted, the macro processes (C_1, C_2 and C_3) influence the PRR and RSSI of all receiver nodes. As mentioned earlier, the nature and extent of the influence of macro process on PRR varies among different receivers. Adding to that, the PRR and RSSI are not directly correlated in each node during the macro processes. This observation can be further elaborated by comparing the relationship between mean RSSI (Figure 3) and PRR values (Figure 2) of nodes N1 and N3. For N1, the mean of RSSI is highest in 'Operation' class C_1 but the PRR of N1 is lowest in the same class C_1. Thus, mean RSSI and PRR have a negative correlation between them. Whereas, for N3, the mean RSSI and PRR are highest in the same class C_1 suggesting a positive correlation. This observation contradicts with observation for N1. Therefore, the two major challenges in developing IDI algorithm for macro processes are a) effect of macro process on nodes are not homogeneous; and b) the relationship between selected features (PRR and RSSI) could be dissimilar.

Possible Approach: With inputs from different nodes, an IDI algorithm running on a macro base station can compute the temporal characteristics of macro schedules such as length and repetition pattern of a process in macro schedule and inform the same to the nodes. The nodes can locally compute the nature and extent of a macro schedule's influence and adapt accordingly.

Applications: An IDI algorithm which predicts macro processes can be used for dynamic network planning such as 1) altering the position of relay nodes, 2) altering the transmit power depending on the expected channel conditions during a macro process.

B. Micro Processes

Local processes of a factory such as machines with rotating components, influence devices communicating in their vicinity. Such processes in a factory schedule constitute 'Micro processes' for a particular communicating device. In the experiment conducted, operation states (s_0, s_1 and s_2) of machine m_5 are considered micro process for node N3 but not for node N1 because operation states of m_5 influences neither PRR nor RSSI of N1.

Challenges & Inference: The effect of different machines on the same node being non-homogeneous and effect of one machine on different nodes also being non-homogeneous is a challenge. Adding to that, nodes experience a combined effect when multiple machines operate simultaneously. This effect is explained in Section IV and illustrated in Figure 5. The consequence of this effect is the explosion in the number of states to be detected and classified by the IDI algorithm. The data available for each micro process analysis was limited because of combined influence of machine operation. Thereby limiting the observations for micro processes.

Possible Approach: Because of the explosion in number of states to be detected, it may be advantageous if an IDI algorithm for micro processes focuses on detecting levels of PRR instead of identifying the source of interference. It would be an interesting future research to study the trade-off between detecting and identifying micro processes.

Applications: An IDI algorithm which predicts micro processes (possibly in milliseconds time scale) can be used for applications such as scheduling of resource blocks for communication.

C. Macro vs Micro Processes

Since the macro processes are slow-changing processes, an IDI algorithm which can predict average channel response will be sufficient. Therefore, resource-constraint nodes may run only an IDI algorithm which detects and analyzes macro process. Furthermore, the schedule of the macro processes can be fed into network by the system administrator and the IDI algorithm can only merely learn the channel response observed during the macro processes. On the other hand, precisely detecting and identifying micro processes are difficult but if possible, it will result in a fine-grained communication optimization.

VI. Conclusions and Future Works

This research experimentally evaluates and provides evidence that operation of machines in a factory-like environment has significant influence on the reliability of IIoT network. On an average, a node's PRR varies by 16%. Certain machines have a positive impact on the PRR of a node ie., a node receives more packet when a particular machine operates, while others have negative or no impact. When multiple machines operate, nodes experience a combined effect. Based on the observations of the experiment, a break down of the processes in factory schedule into macro and micro processes depending upon the time-scale of a process is defined. The challenges in designing an IDI algorithm for macro and micro processes are elaborated alongside possible approaches to tackle them. Apart from the discussion in Section V, it is advised to set-up a well planned and controlled experiment and to perform extensive analysis into communication and computational overhead. Developing controlled environment can be justified by the fact that the machines and floor plan of a factory floor rarely changes. Once the network/IDI mechanism learns the effect of different machines, the knowledge obtained can be utilized for reliable communication. This research is a first step towards a more profound development of adaptive networks to increase the reliability of an IIoT system.

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