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Empirical IIoT Data Traffic Analysis and Comparison to 3GPP 5G Models

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***Abstract*—5G New Radio (NR) technology is expected to enable the wireless transition of manufacturing processes in modern factories. In order to proper dimension the 5G system, accurate models of the data and control traffic in industrial use cases are needed. In this paper, we analyze the industrial traffic empirically measured in different Danish factories and compare its characteristics to the modeling assumptions used in the 3GPP for 5G NR performance analyses. In particular, three relevant use cases are studied: a unit test cell for actuator calibration, a visual inspection cell, and the control of an autonomous mobile robot (AMR). Our results indicate that some of the relevant 3GPP assumptions for industrial traffic such as exponential packet-interarrival time (PIAT) for aperiodic traffic and fixed packet sizes are only partially corroborated by experimental evidence. Moreover, industrial traffic can exhibit a large burstiness that may lead to conservative admission control and radio resource allocation.**

I. Introduction

The fourth industrial revolution (I4.0) is the next step in manufacturing. Numerous emerging technologies ranging from big data and artificial intelligence to matrix-based production and autonomous mobile robots, are expected to bring value creation through new services or increased production output [1]. A prerequisite for the agile vision of I4.0 is wireless communication, allowing for reduced deployment costs as well as more flexible and scalable production environments. Dimensioning a wireless system to operate specific industrial applications requires insight into specific communication requirements which in turn must be analyzed, modelled, and validated.

5G New Radio (NR) is considered a strong candidate for providing wireless industrial communication, as it is designed to support a broad set of requirements, including millisecond-level latencies with five nines reliability. The 3rd Generation Partnership Project (3GPP) standardization body and advisory bodies such as 5G- Alliance for Connected Industries and Automation (5G-ACIA) have worked together with industrial verticals to define the proper application scenarios and traffic models that are used in the design and evaluation of 5G Industrial Internet-of-Things (IIoT) systems [2] [3]. However, as highlighted in [4], there is still work to be done in terms of definition of industrial use cases, their associated communication requirements and traffic models.

While the existing models can provide a valid starting point for the analysis of relevant wireless use cases, they may indeed fail in reproducing critical aspects of real-world deployments and scenarios. This may result in incorrect dimensioning of the wireless system accomplishing specific tasks, leading to over-provisioning of the radio resources or in the worst case in under-performing solutions, which could be showstoppers to the support of critical applications.

Experimental verification of the characteristics of industrial traffic in relation to established models is therefore needed. In this respect, there is little scientific literature reporting traffic measurements of industrial use cases under operational conditions. In [5], the authors present models for several different Ethernet-based use cases based on measurements of a testbed for flexible manufacturing processes. While the authors report the final parametrization of the models, there is a lack of insight on the actual measurements and underlying industrial communication. A method for analyzing industrial data traffic is presented in [6]. However, the analysis is limited to supervisory control and data acquisition (SCADA) traffic and Skype calls and lacks discussion on the suitability of existing radio technologies and their respective modelling approaches. Related to data traffic characterization, but in a different non-industrial context, [7] presents a thorough analysis and classification of data traffic patterns in public networks.

In general, the existing literature presents simplified findings from measurements performed over non-industrial networks or semi-artificial system setups. This paper aims at shedding some light into the topic, by providing an extensive empirical analysis of control data traffic flows obtained from real industrial factory machinery in operational conditions. Further, this paper verifies to what extent existing 3GPP modelling assumptions reflect real world scenarios, and identify further relevant aspects in the traffic behavior, not accounted by current models, that are to be considered when dimensioning the wireless system. We base this upon empirical analysis of traffic measurements for three relevant industrial use cases performed in different operational Danish factories. Specifically, we study the cases of an unit test cell for quality insurance, a visual inspection cell, and manual or fleet operated control of an autonomous mobile robot (AMR). Through the analysis we compare traffic distribution, packet sizes, and burstiness characteristics against 3GPP models and assumptions used as part of 5G NR IIoT studies.

It is worth mentioning that it is not in the scope of the paper to generalize the results of our analysis, neither to derive new

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traffic models, as this would require more thorough and extensive studies. We believe however this paper can represent a starting point for traffic characterization in industrial scenarios, which may lead in the future to tailored traffic models to be used in performance evaluation of novel IIoT concepts.

The rest of the paper is structured as follows. Section II introduces the main modelling assumptions and metrics for traffic characterization in industrial scenarios as defined by the 3GPP. Section III describes the measurement approach and the studied use cases. Section IV presents the traffic statistics extracted from the traces along with a discussion on how these compare with the 3GPP models and assumptions. Finally, conclusions are summarized in Section V.

II. Modeling of IIoT traffic in 5G

As baseline for standardization work for 5G in IIoT, many studies were done to define use-cases and typical application traffic behaviors and requirements for the factories of the future [2]. Reference use-cases include for instance motion control, control-to-control communication, mobile robots, human machine interfaces, process automation, and monitoring. The applications vary significantly in terms of their requirements for service availability, packet reliability, packet latency, and throughput levels. In the following, the traffic models used most often in 5G IIoT studies are presented as well as the parameters that are used to describe traffic characteristics and their requirements within the 5G system, i.e. the 5G Quality of Service (QoS) model.

A. IIoT traffic models

In spite of large differences between IIoT applications, only few simple models are commonly used when evaluating 5G performance for such applications as illustrated in Table I, i.e. periodic and aperiodic traffic models. The periodic model uses a fixed packet size and fixed packet inter-arrival time (PIAT) (i.e., fixed periodicity) and the relative phase or time offset between different flows may be modeled [8]. In the case of aperiodic traffic, the standard model assumption used in 3GPP is the FTP model 3 [9]. This assumes fixed packet size with Poisson arrival, resulting in exponentially-distributed packet inter-arrival times as follows:

$$\text{PIAT} \sim \text{Exp}(\lambda), \tag{1}$$

where λ is the average packet rate. Using this assumption, the traffic is memory-less; meaning that there is no correlation between PIAT values for consecutive packets.

TABLE I
Typical traffic models used in 5G IIoT standards research

Characteristic	Periodic model	Aperiodic model
Packet size	Fixed	Fixed
Packet spacing	Fixed	Statistical
Transmission	Unicast	Unicast

B. 5G QoS model

For characterizing the aperiodic traffic, the 5G QoS framework defines further parameters and metrics [10]. In 5G, a QoS flow is defined as a stream of packet(s) between two endpoints which pertains to the same application [10], [11]. A pair of endpoints can have multiple QoS flows in parallel, but each flow uses its own distinct traffic model. In case a packet stream is multicast or broadcast oriented, the 5G system acts as a proxy and translate this single stream into multiple distinct unicast QoS flows, which means that from a modeling perspective there is no difference.

Depending on the traffic flow resource type, only selected QoS parameters are used to describe the packet stream. For traffic flows with strict delay control requirements (such as the ones observed in factories), the Delay-critical Guaranteed Bit Rate (GBR) QoS Flow type is expected to be used. For this resource type, the following metrics are of importance when configuring the 5G system: Priority Level, Packet Delay Budget (PDB), Packet Error Rate, Averaging Window (AW), Maximum Data burst volume (MDBV). The MDBV is defined as the maximum data burst that needs to be delivered within any given PDB. A mathematical model for MDBV can be formulated as:

$$\text{MDBV}(\text{PDB}) = \arg \max_{t_0 \in \mathbb{R}_{\geq 0}} \int_{t=t_0}^{t_0+\text{PDB}} b(t) \cdot dt, \tag{2}$$

where $b(t)$ describes the incoming data at time t (Bytes).

For a QoS flow, another metric, the Guaranteed Flow Bit Rate (GFBR) denotes the required maximum data rate of the flow averaged over the AW, where AW has an average value of 2 seconds [10]. For IIoT type traffic, the allowed failure rates are very low, often 0.0001% or lower. A failure for the Delay-critical GBR QoS resource type is defined when all of the following conditions are fulfilled [10]:

- A packet is delayed by a value greater than PDB,
- the data burst over the period of PDB has not exceeded the MDBV, and
- the QoS Flow is not exceeding the GFBR in the current sliding window.

Specifically for periodic traffic, 5G introduces Time Sensitive Communication Assistance Information (TSCAI), enabling each gNB to know which periodicity (Periodicity) and at which time-offset (Burst Arrival Time) traffic arrives [10]. As shown in [8], this information is helpful to configure resources for UE in advance to reduce the latency, especially in uplink, but also in configuring semi-static resources that allows for significant optimization of the 5G spectral efficiency.

For the sake of this study, we introduce the Average Data Burst Volume (ADBV) which is similar to the MDBV above except it is defined as the average volume of all windows within a measurement period where data is present. Comparing the ADBV to the MDVB as well as the GFBR provides some additional insights into the burstiness of the observed data flow. Further, we have generalized the MDBV as we do not know the effective PDB for the studied applications and thus the

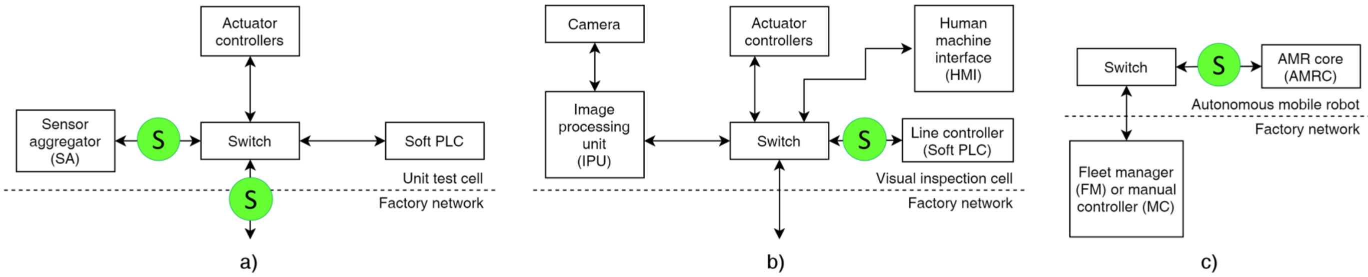

Fig. 1. Overview of the network architectures and traffic sniffing measurement points (S) for the selected use cases: a) unit test cell, b) visual inspection cell, and c) autonomous mobile robot.

specific window for which the MBDV should be evaluated over. Instead, we report MDBV statistics for a selected range of windows [1, 2, 5, 10, 100] ms.

III. Industrial Use Cases

Three uses cases are considered for our empirical traffic analysis. Such use cases have been selected according to their IIoT relevance but also due to the granted permissions for accessing the factory premises - it is not often the case in which factories are willing to share their use cases, control systems and grant permission to interface their machinery for obtaining an overview of the control data traffic as, apart from control data, there are typically other production-confidential information in those exchanges of information.

Data traffic measurements were obtained by interfacing a ”sniffer” to selected machinery Ethernet-based network links where the control data is flowing. The sniffer device used was an evolution of the one previously presented in [12] and it logs all protocol headers at layers 2 and above while remaining transparent to the underline application. No packet inspection is performed on the packets, conserving the confidentially of the production business-critical data. The sniffer introduces a calibrated extra latency not larger than 0.5 ms due to the input-output bridging and the data logging process. The sniffer performs reliable measurements (no packet losses) for packets of up to 1500 B size and packet inter-arrival times larger than 10 μs. The introduced latency is generally constant (with a processing delay jitter <30 μs) and therefore, inter-arrival packet measurements are not affected by the measurement procedure.

A. *Unit Test Cell (UTC)*

We measure the traffic in a quality assurance unit test cell, whose main task is to provide calibration and tolerance figures for an actuator that the company uses in their final product. The network architecture related to this use case is illustrated in Fig. 1.a, where the position of the sniffers (S) is highlighted with green circles. For further reference, a picture of the machinery control networking setup is shown in Fig. 2.a. A soft Programmable Logic Controller (PLC) acts as supervisor of the cell operations. An actuator is placed in a test rig, where it is activated by the soft PLC according to a specified control sequence. A set of sensors continuously measures the device

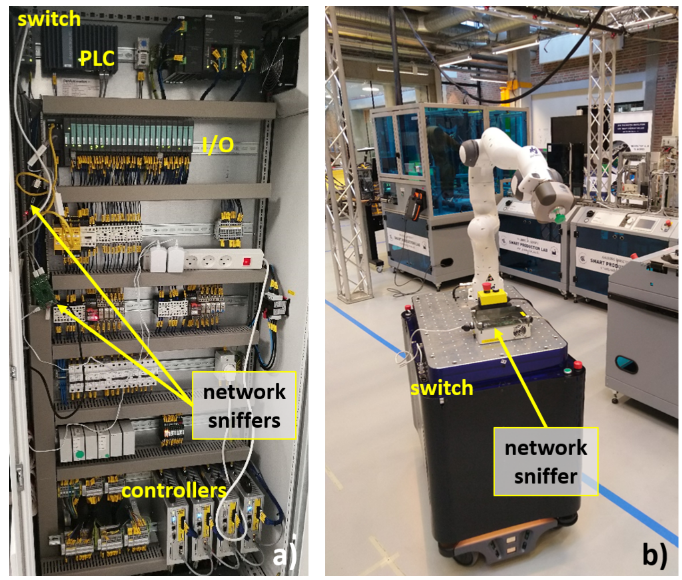

Fig. 2. Overview of industrial measurement setups for two of the use cases: a) unit test cell, and b) autonomous mobile robot. Unfortunately, we are not allowed to disclose any picture related to measurement of the visual inspection cell use case.

performance and report such measurements to the soft PLC. Once the test sequence is finished, the collected results are reported by the soft PLC to a factory level common database.

The first sniffer is placed in between the soft PLC and the sensor aggregator (SA), thus capturing the sensing part of the control cycle. The second sniffer is placed in between the cell and the factory network capturing all the traffic going to and from the cell from a factory network perspective.

B. *Visual Inspection Cell (VIC)*

This use case consists of a cell which is also performing quality assurance, but this time, by means of video feeds from a camera located in proximity of a conveyor belt transporting parts for final assembly. The network architecture of this use case is illustrated in Fig. 1.b. The live feed from the camera is streamed to a image processing unit (IPU), that performs quality control tasks. Here, the images are compared to the ones stored in a collection of successfully assembled product, in order to detect possible relevant discrepancies. Based on the outcome, a command is forwarded to the line controller/soft PLC, which is the centralized reference or main brain of the cell, that then dictates the operation of the robots in the assembly line by sending proper commands to the actuator controllers. For example, in case the product part is deemed to be faulty, the robots remove it from the conveyor belt. Conversely, in case the quality of the product part fulfills the specification, the robots forward it to the next manufacturing cell. Throughout the process, status updates are sent from the soft PLC to a human machine interface (HMI) device, for general monitoring purposes.

In this case, we measure two traffic flows by probing with the sniffer the link between the line controller and the cell main switch: one between the soft PLC and the IPU, and another between the soft PLC and the HMI.

C. Autonomous Mobile Robot (AMR)

The third use-case considers AMRs, which are robot vehicles, typically used for logistics within production, that can move materials across the factory space without using pre-marked routes, but rather relying on Light Detection And Ranging (LiDAR) or optical technologies to self-navigate between target positions. The network architecture and control traffic measurement setup for this use case are illustrated in Figs. 1.c and 2.b, respectively. The considered AMR use case considers has two different operational configurations:

1) Fleet manager (FM) mode, where a central entity (manager) allocates robots to perform certain automated tasks in the factory.
2) Manual controller (MC) mode, where a human is manually-controlling and guiding the robot via tablet or phone.

In fleet mode, the manager is requesting telemetry and status information at regular intervals from each robot and receives updates from the robots as they reach objectives or complete assigned tasks. In manual mode, the robots transmit to the operator a map of the local environment together with its position, including live updates of any detected obstacles. From the operator side, communication consists of manual control input from a supervision tablet, besides task commands from a predefined set of actions.

The AMR represents a clear example of a wireless use case. In live operation, the connections between the AMR operation core (AMRC) and the FM and MC would happen via factory floor Wi-Fi. Therefore, to capture the application control data traffic without the intrinsic effects of a wireless connection, a sniffer was placed in between the AMR core and the PC hosting both the manual control and the fleet manager software, interconnected via gigabit Ethernet.

IV. Results & Discussion

In this section, the traffic analysis of the different use cases is presented. Measurements are obtained via our traffic sniffers as described in section III. Performance is discussed based on the parameters presented in Section II on a per use case basis and based on the traffic flow to (←) and from (→) a specific target. Relevant bi-directional (↔) data flows between two devices are also addressed in some cases. Emphasis is given to those cases exhibiting very tight inter-arrival times - in the order of 1-10 ms and below, which can represent cases of critical IIoT traffic if associated to a tight PDB.

Results for the unit test cell, the visual inspection cell and the autonomous mobile robot are displayed in Figs. 3, 4 and 5, respectively. In each of these figures, sub-figure a) refers to the PIAT statistics, while sub-figures b) and c) refer to the packet size statistics, and the MBDV and ADBV behavior, respectively. As we do not know the specific effective PDB for most of the cases and, therefore, the specific windows over which the MBDV should be evaluated over remains also unknown; we report statistics for a selected range of windows [1, 2, 5, 10, 100] ms. This is meant to capture the network requirements in terms of traffic to be supported for a diverse set of PDBs.

A. Individual Use Case Results

1) Unit test cell: When examining the results for the unit test cell as presented in Section III, there is a clear distinction between the cell ↔ factory and the PLC ↔ sensor aggregator (SA) flows - see Fig. 1.a. The staircase-like behavior of the cell ↔ factory traffic PIAT in Fig. 3.a, stems from the presence of periodic inter-cell broadcast messages which make up the majority of the packets observed within the traffic traces (∼90%). Similar tendencies are also observed for the packet sizes in Fig. 3.b as there are three distinct values (60, 234, and 637 bytes) that occur each with a different probability. When examining the MDBV as compared to the ADBV in Fig. 3.c, a different of an order of magnitude is observed, suggesting that dimensioning the system based on the MDBV would result in a potential over-dimension of resource allocation. Regarding the PLC ↔ SA flows, the periodic nature of the traffic is clear. A 2 ms cycle is observed in Fig. 3.a, although with minor deviation at the lower percentiles which is due to the initial setup and control messages. The flows have fixed packet sizes (96 and 113 bytes) that are directional-dependent. The ADBV and the MDBV curves in Fig. 3.c are, in this case, relatively close to each other compared to the cell ↔ factory case, due to the traffic being nearly periodic and with limited variability in the packet sizes.

2) Visual inspection cell: As the traffic in this cell appears clearly non-periodic, together with the PIAT statistics in Fig. 4.a, their associated 3GPP model-based exponential (exp) inter-arrival time distributions are also displayed - the model was fit based on the mean PIAT calculated upon the empirical data. Such exponential distributions exhibit a good match with the IPU ↔ PLC traffic for inter-arrival times in the order of 1 ms and above, while representing a pessimistic estimate of the effective traffic for more critical timings. For the HMI ↔ PLC case, the exponential distribution appears even more pessimistic, with the exclusion of the PIAT values at the top end. The HMI ↔ PLC packet sizes displayed in Fig. 4.b, range from 128 bytes up to 512 bytes in downlink and 100 bytes to 250 bytes in uplink. For the IPU ↔ PLC traffic, the packet

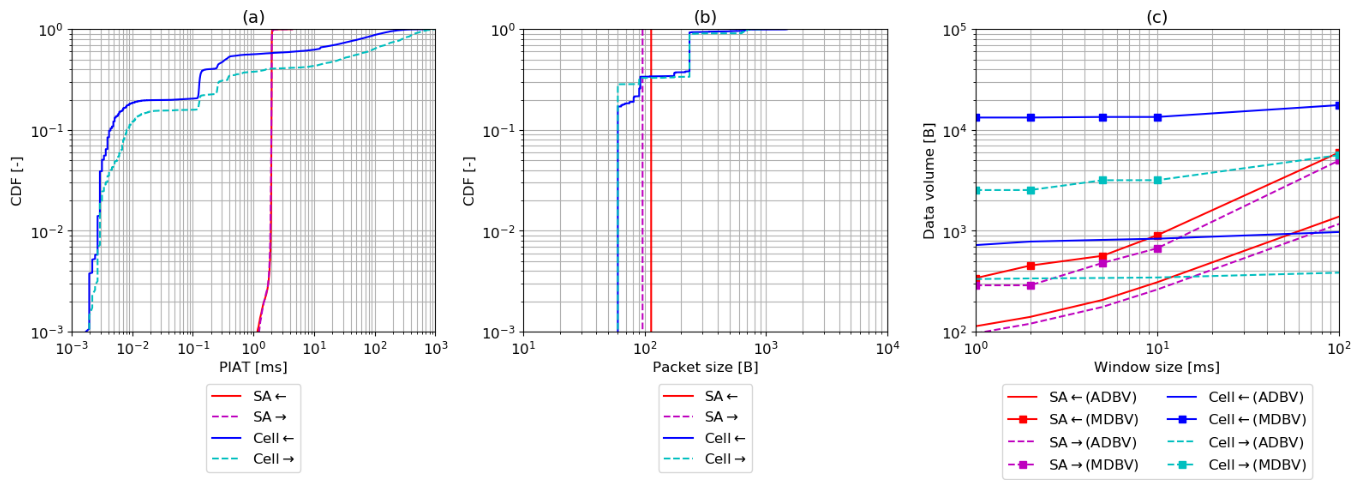

Fig. 3. Measurement results from the unit test cell flows: a) statistical distribution of the PIAT, b) statistical distribution of the packet size, and c) ADBV and MDBV estimation for different window sizes.

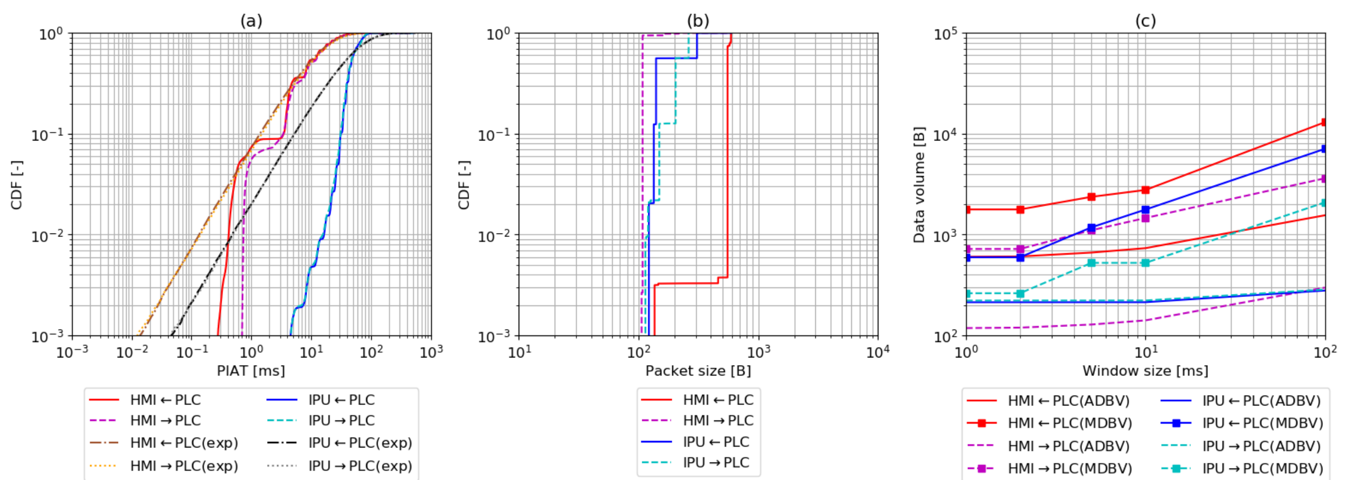

Fig. 4. Measurement results from the visual inspection cell flows: a) statistical distribution of the PIAT, b) statistical distribution of the packet size, and c) ADBV and MDBV estimation for different window sizes.

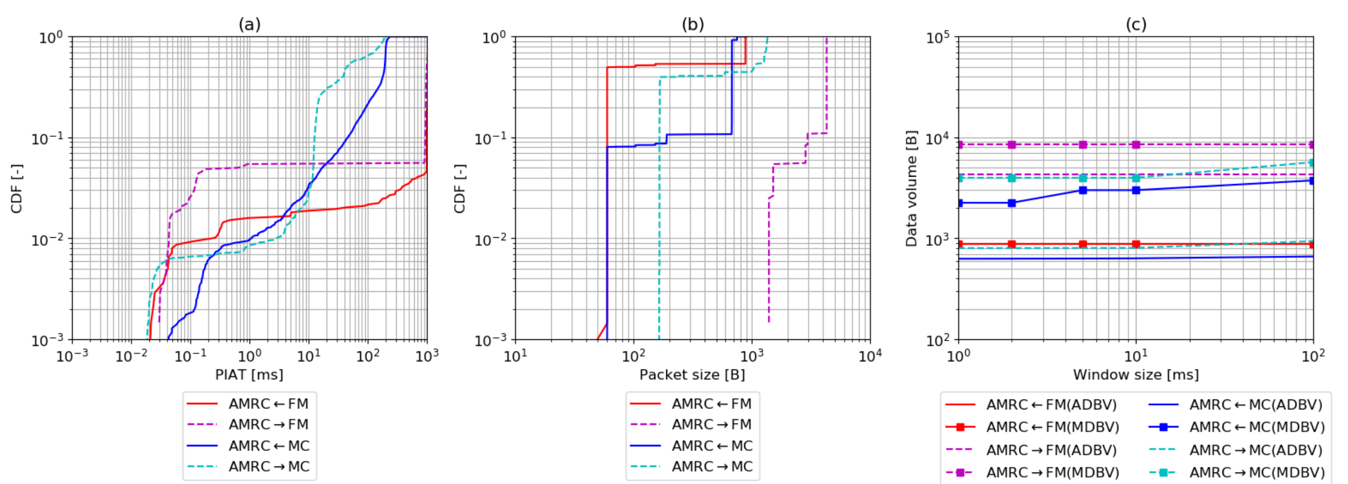

Fig. 5. Measurement results from the AMR control flows: a) statistical distribution of the PIAT, b) statistical distribution of the packet size, and c) ADBV and MDBV estimation for different window sizes.

TABLE II
SUMMARY OF THE MAIN DATA TRAFFIC STATISTICS, INCLUDING FLOW META DATA, FOR THE DIFFERENT USE CASES AND CONTROL FLOWS.

Use case, control data flow	Inter-arrival time [ms]			Packet size [B]			Protocol statistics [%]		Throughput [kB/s]
	min	max	median	min	max	median	BC/UC	UDP/TCP/Other/Industrial	avg/GFBR
UTC, SA←	0.007	2000	2	60	1506	96	4.5/95.5	3.3/1/<1/95.6 (Profinet)	49/48
UTC, SA→	0.002	300	2	42	1506	113			50/56.6
UTC, Cell←	0.002	1055	26	60	950	234	90.3/9.7	66.8/<1/31/1.7 (Profinet)	5.7/26.2
UTC, Cell→	0.02	382	2	42	1496	174			1.5/7.9
VIC, IPU←PLC	2.86	508	47	82	596	140	8.3/90.7	4.1/0/<1/95.5(ENIP)	4.1/29.5
VIC, IPU→PLC	1.58	508	46	82	262	204			4.2/8.2
VIC, HMI←PLC	0.009	382	9	82	592	554	0.8/99.2	0.9/0/<1/98.2(ENIP)	42/57.7
VIC, HMI→PLC	0.128	443	10	82	582	108			9.4/13.5
AMR, AMRC←MC	0.021	3584	193	42	901	678	1.7/98.3	<1/98.3 (REST)/0/0	10.3/19.9
AMR, AMRC→MC	0.007	251	44	155	1422	1047			3.8/8.8
AMR, AMRC ←FM	0.021	15817	1003	42	883	104	0/100	0/100 (REST)/0/0	4.3/10.7
AMR, AMRC→FM	0.030	1094	996	1396	4292	4292			0.8/1.3

sizes ranges from 100 bytes to 200 bytes for both uplink and downlink. The ADBV and MBDV analysis in Fig. 4.c, shows higher data volume for HMI ↔ PLC traffic. The difference between ADBV and MDBV reflects a certain traffic burstiness for both HMI ↔ PLC and IPU ↔ PLC flows, but not as dramatic as in the previous UTC case.

3) Autonomous Mobile Robot: The fleet manager is generating periodic polling commands (FM ↔ AMRC flow); however, the PIAT values shown in Fig. 5.a are not periodic due to variability of response time of each AMR, which affects both input and output communication flows. This is due to non deterministic processing time at each robot, as well as to the implementation of the control application (based on REST interfaces). MC ↔ AMRC traffic shows critical components with tight inter-arrival times; such inter-arrival times are rather heterogeneous due to the specific underline application process (e.g., image transmission) and behavior of the REST APIs. Packets to and from the fleet are either very small (around 60 bytes) or in the order of 1 kilobyte and above (Fig. 5.b). For the MC ↔ AMRC mode, such big packets can be due to the images that are streamed to the operator, as well as to the potential inefficiency of underline protocol design. For this AMR use case, the data volume is fairly insensitive to the window size (Fig. 5.c). This is due to the nature of the traffic, composed mainly of periodic components. Some dependency is only visible for the manual case, due to the inherent variability of the data traffic (image transfer). Also, no major differences between MDBV and ADBV are visible.

B. Summary of traffic statistics

Table II summarizes the main statistics extracted from the figures above, together with some extra reference information related to flow throughputs and other metadata such as protocol types and broadcast/unicast ratios. In particular, the classification of traffic nature and layer 3 and above characteristics are highlighted.

Regarding the unit test cell, as expected the sensor aggregator traffic is mainly dominated by unicast packets, and traffic type is industrial, mainly consisting of the PROFINET protocol. Conversely, the ingress/egress cell traffic is dominated by broadcast packets, and mainly composed by UDP packets due to keep-alive heartbeat signals. Regarding the visual inspection cell case, the IPU traffic is mainly unicast, and composed in a major part by industrial specific protocols, i.e. Ethernet Industrial Protocol (ENIP), besides standalone TCP packets. The HMI traffic is almost entirely unicast and also composed by ENIP packets. AMR traffic is only unicast and entirely TCP.

C. Comparison with current 3GPP 5G IIoT models

In some use cases (unit test cell, autonomous mobile robot), the traffic appears to be dominated by periodic components. A composite model of the traffic flow is therefore needed to capture such dynamics. This could be obtained by combining multiple 3GPP periodic models with different periodicity. Generally, when measuring between two end-points, the overall traffic is a combination of multiplexed data flows, as for e.g., the ”Cell→” link in the UTC use case. To link those measurements to the 3GPP models, which work on a per-flow basis, it is important that those flows are first demultiplexed and only then mapped to 5G QoS flows, each with more balanced parameters and proper setting of the PDB.

For aperiodic traffic as in the visual inspection cell - see Fig. 4.a, the results indicate that the used FTP Model 3 for 5G IIoT studies in the 3GPP has only a partial match with the traffic flows of HMI and IPU. For very critical PIATs, the exponential assumption has a different curve slope compared to the real inter-arrival data extracted from the measurements. In some cases, the fitted FTP Model 3 leads indeed to a significant over-estimation of the inter-arrival times of the traffic. The model therefore does not reflect accurately the dimensioning requirements for the network and is hard to tune to the observed traffic flows. Further, variable packet size instead of fixed packet size should be considered as part of the traffic modeling as this was the case for most of studied data flows.

Examining the GFBR for the various use-cases and flow directions, presented, we observe that the GFBR is generally similar to the average throughput measured over the entire measurement period, with the exception of a few use cases (e.g. ”IPU←” link in the VIC use case) where GFBR can be up to 8 times higher. The deviations suggest that there is some burstiness in the data traffic as also indicated by the MDBV and ABDV analysis. To fully explain the burstiness, deeper insight into the application and protocol behavior is required which is left for future work.

The window size for MDBV calculations in 3GPP typically corresponds to the PDB. When considering for instance a 10 ms window size, the MDBV in Fig. 1.c for the "Cell→" UTC link is just above 1000 bytes meaning that data arriving within a single window have a corresponding instantaneous data rate of about 100 kB/s an ADBV rate of 29 kB/s, whereas the data rate averaged over the entire measurement period is only 1.5 kB/s. Such a large discrepancy between the MDBV, the ADBV and the average bit rate is challenging in the modeling as well as for the dimensioning of the wireless system and may lead to conservative admission control and resource allocation mechanisms. Better characterization could be done by including an additional parameter for the delay-critical GFBR resource type which describes the discrepancy between MDBV and ADBV defined over the PDB.

V. Conclusion

In this paper, we have studied the control data traffic characteristics of three industrial use cases (unit test cell for quality assurance, visual quality inspection of raw products, and autonomous mobile robot) based on empirical measurements obtained in Danish factories. Traffic has been statistically analyzed in terms of inter-arrival packet time, packet size, and burstiness along with the used protocols, and compared with 3GPP assumptions for 5G IIoT system design.

Our analysis revealed that the traffic in industrial scenarios is significantly more heterogeneous than what has been considered as baseline in the 3GPP. Exponential distribution for packet inter-arrival times has in the best case a limited match with the actual experienced traffic, and it may lead to an underestimation of the required resources for successful wireless communication. Moreover, packet sizes are rather diverse. Furthermore, analysis of the burstiness show large variability between average and maximum data burst sizes which may lead to e.g., conservative admission control and resource allocation. Protocol analysis showed that broadcast packets represent a major fraction of the overall traffic in the unit test cell use case. As in 5G NR broadcast traffic is divided into unicast flows, proper care should be taken when handling wirelessly this type of traffic.

This paper is intended as a starting point for industrial traffic characterization activities. In this respect, it was not in the scope of the paper to propose an updated model for 5G IIoT traffic, but rather to identify the need for a more careful analysis of data traffic in real use cases, moving beyond the generic 3GPP models. A further set of measurement campaigns in a comprehensive set of scenarios is needed for the sake of designing accurate traffic models for 5G IIoT.

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