A ML-based Spectrum Sharing Technique for Time-Sensitive Applications in Industrial Scenarios

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***Abstract*—Industry 4.0, driven by enhanced connectivity by wireless technologies such as 5G and Wi-Fi 6, fosters flexible industrial scenarios for high-yield production and services. Private 5G networks and 802.11ax networks in unlicensed spectrum offer very unique opportunities, however existing techniques limit the flexibility needed to serve diverse industrial use cases. In order to address a subset of these challenges, this paper offers a solution for time-sensitive application use cases. A new technique is proposed to enable data-driven operations through Machine Learning for technologies sharing unlicensed bands. This enables proportionate spectrum sharing informed by data to improve critical applications performance metrics. The results presented reveal improved performance to serve critical industrial operations, without degrading spectrum utilization.**

***Index Terms*—5G, 802.11ax, Spectrum Sharing, Contention Window, Time-Sensitive Applications**

I. Introduction

The ongoing industrial revolution, known as "Industry 4.0," is driven by digital transformation, enabled by advanced connectivity, artificial intelligence, and robust computing power. Wireless communication in smart industrial processes fosters flexibility, enabled by technologies such as 5G and Wi-Fi 6, enhancing system performance for high-yield manufacturing. To drive the needed digital transformation for Industry 4.0, private 5G networks are increasingly being deployed offering enhanced reliable connectivity, improved security, and better control of network management and automation. Similarly, recent amendments to the IEEE 802.11 standard have received wide acceptance and deployment in industrial settings. However, to leverage the return on investments, particularly from private 5G networks, unlicensed spectrum offers free-to-use spectrum which makes deploying these networks a cost effective option.

Despite the benefits these technologies bring to smart industrial processes while operating over the unlicensed spectrum, some fundamental challenges are raised [1]. One of the challenges is, that the spectrum channel needs to be shared by multiple wireless devices operating different radio access technologies (RATs). Specifications have been defined to support different spectrum sharing schemes to promote fair coexistence between RATs [2]. While some concerns still remain regarding the potential impact on each technology's performance, novel approaches and techniques are still required to enable data driven operations of coexisting technologies in unlicensed bands. Based on this need, we present a technique which enables intelligent spectrum sharing for efficient operations in industrial scenarios, where critical and time-sensitive equipment, are granted sufficient spectrum resources over less critical devices. The aim is to meet the functional requirements for critical applications while providing relatively better performance for less-critical applications. We propose applying the Uniform Difference Distribution (UDD) function to establish the distribution of the idle-time interval between transmissions for coexisting nodes over the channel. This distribution enables the determination of per node and system data-rates and transmission delay based on the number of contending nodes over the channel. Leveraging this distribution, we propose the machine learning models to decide the optimal contention window (CW) to support the time-senstive applications.

Several studies have applied artificial intelligence to spectrum sharing problems in coexisting scenarios, which addresses different issues. The work presented in [3] focused on establishing the number of Wi-Fi BSS contending over a channel. This is crucial for implementing any practical fair spectrum sharing scheme. Tested using 3 different deep learning models, a very high accuracy was achieved. In [4] and [5] reinforcement learning and deep reinforcement learning techniques were applied to establish fair opportunistic access and improve channel assignment for better throughput and resource utilization respectively. While other works only focus on fair opportunistic access, our work distinguishes itself by emphasizing efficient spectrum sharing with a consideration for service priority.

II. Scenario and System Model

In this section, we describe the industrial scenario adopted, time-sensitive and delay tolerant applications considered for critical operations and system monitoring respectively. A system model that elucidates key network parameters and protocols for 5G NR-U and IEEE 802.11ax are also given.

A. Scenario Description

A segment of industry experiencing significant advancement is the recycling industry. Material Recycling Facilities (MRFs) are opening, equipped with state of the robotics and AI technologies to sort a wide range of disposed materials. To sort these materials, video technology and computer vision techniques are utilized. In this paper, we consider a scenario where high resolution videos are captured and streamed real-time to an edge-cloud server for critical processing workloads. The time-sensitiveness of sorting these materials require timely transmission of the video to the edge-cloud where object detection tasks are completed to aid robotic arms in sorting the materials identified. Having the ML model located on the edge-cloud, offers the advantage of higher computing resources and continuous learning to evolving data, enabling the MRFs capacity to process more diverse waste. The potential to expand its sorting capacity, means the number of robotic arms sorting materials can increase over time. Also, situations may arise where the MRFs are running at reduced capacity, hence a flexible and adaptive technique, informed by situational awareness and application requirements, ensure critical operations are not negatively impacted. Given the time synchronise functions in sorting the waste materials, a data rate and delay threshold is required in ensuring expected performance.

B. Network Model

The MRF's sorting floor considered has a dimension of 120m by 80m. It utilizes a conveyor belt system where the recycled materials are sent to be processed and sorted by robotic arms into different categories. The network model adopted, consists of a private 5G network with two 5G NR-U gNodeB base-stations and two 802.11ax Access Points (APs). The performance of the proposed spectrum sharing technique is evaluated based on number of connected User Equipment (UE) transmitting video/control data from/to the robotic arms and Stations (STAs) transmitting system facility data to digital dashboards distributed across the MRF. The UEs and STAs located at fixed locations are connected to the gNodeBs and APs respectively. The robotic arms equipped with ultra high-definition (UHD) cameras with machine vision capabilities are connected to the 5G NR-U network to exploit enhanced network functionalities. Similarly, digital displays and dashboards distributed across the sorting floor are connected to the 802.11ax based Wi-Fi network. Given the industrial scenario adopted for our proposed solution, the transmission between the wireless nodes can be obstructed. Consequently, the 3GPP InF channel model is utilized in obtaining the received signal. In [6] the 3GPP InF model was validated within a real world factory environment. For 802.11ax, the TGn and TGac spatial channel model were adopted for 802.11ax indoor channel models according to [7] and applied in [8]. The pathloss model considered in this paper for the 802.11ax network are according to channel model E for indoor Large Office/Warehouse scenarios. Based on both channel models, the 5G NR-U and 802.11ax networks are designed to achieve a minimum modulation and coding scheme (MCS) of 256 QAM, operating over a 40MHz channel, with gNodeB/AP transmit power at 30dBm and UE/STA at 24dBm. The spectrum sharing approach in this paper investigates performance of co-channel coexistence, which requires all nodes to be detectable through spectrum sensing during the clear channel assessment (CCA).

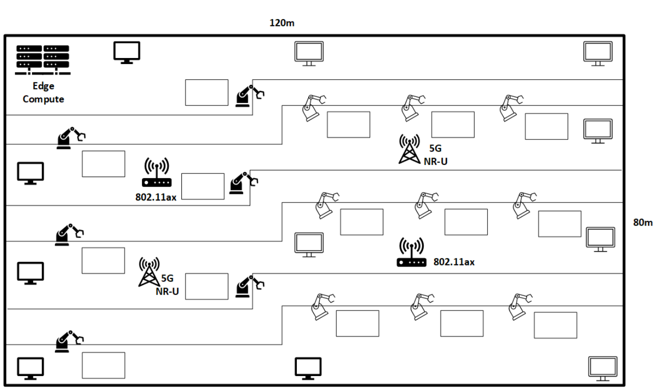

Fig. 1. Network layout of MRF with 5G NR-U and 802.11ax networks operating in unlicensed bands

C. Traffic Model

To enable enhanced sorting capabilities at the MRF, multiple video resolutions are adopted similar to [9]. It is shown in [10] that with their technique, 4K video can be down-scaled to lower resolution videos, and still achieve good Average Precision (AP). 4K video is adopted with the feature to downscale or adapt to multiple bitrate for object detection tasks when necessary. We consider multiple adaptive bitrates configurations via High Efficiency Video Coder (HEVC) codec, subject to achievable Average Precision (AP) according to work done in [9]. Based on their work, we select a bitrate threshold of 15Mbps, 20Mbps, 25Mbps, 35Mbps and 75Mbps. These bitrates achieved over 80% AP in object detection tasks. Adaptive bitrate is crucial to offer varied compression, influenced by changing spectral resources subject to the number of robotic arms in operation at a particular period. A balance must be struck to ensure fast decoding and object detection at the edge-cloud and achieving high AP to fit the available spectral resources. Hence, ensuring an optimal data-rate sufficient to support the highest video encoded bitrate as much as possible. One 4K camera is attached to the robotic arm, with video capture at (3840x2160) resolution, 8bit RGB, 15 fps, at an uncompressed bitrate of 373.2 Mbps. Adaptive bitrate between 15 Mbps to 75 Mbps are considered in the performance evaluation.

D. IEEE 802.11ax System Model

PHY Abstraction - To evaluate the performance of the proposed technique, the IEEE 802.11ax standard is utilized. The PHY and MAC layers are the crucial parts in the WLAN technology. An abstraction of the PHY layer is adopted, which has been substantively validated in MATLAB for link-level and end-to-end simulations [11]. The data rate achievable is based on the number of transmitted bits across the spectrum over a given period of time.

$$S_{(w)} = \frac{\sum_{i=1}^{D} (\chi^{w}) \cdot \sum_{j=1}^{S} \sum_{k=1}^{C} (b^{w}) \cdot (r_{k}^{w}) \cdot (\eta^{w})}{\tau_{(\kappa)} + \tau_{(\gamma)}} \tag{1}$$

In (1), the data rate $S_{(w)}$ is subject to the number of data subcarriers χ within the chosen channel bandwidth. The coded bits per subcarrier b, applied channel coding r, across spatial streams η, over a given symbol duration $\tau_{(\kappa)}$ and guard interval $\tau_{(\gamma)}$, altogether give the link-level data rates. The PHY abstraction applied in this paper, adopts a basic data transfer unit of 1ms. This is sufficient given the minimum transmission opportunity (TXOP) applied is (5ms). In the evaluation undertaken, OFDMA is not used, hence each transmission opportunity is dedicated to a specific station.

MAC Model - The channel access management is controlled by the MAC layer. It performs an opportunistic channel arbitration, through a random process via a uniform distribution. A back-off integer is selected within the contention window (CW) and is decremented by 1 every slot interval ω ($9us$) while the channel is idle, till it reaches zero; at this point a transmission is attempted over the idle channel. If a collision is detected, the CW size is doubled till a maximum CW_{max} and this continues until a successful transmission is achieved.

$$\rho_{(n+1)} = \begin{cases} 0 & \text{Wi-Fi Transmission} \\ > 0 & \text{Backoff counter decrement} \end{cases}$$

ρ is the back-off integer selected for each arbitration cycle for transmission. Once ρ reaches zero a transmission is attempted, otherwise the backoff counter decrements while the channel is idle. An acknowledgement (ACK) frame is transmitted if a transmission is successful after a short interframe space (SIFS).

E. 5G NR-U System Model

PHY Abstraction - Similarly, to obtain the system data rates for 5G NR-U a PHY layer abstraction is used to compute the attained data rate per node, when LBT procedure is applied for channel contention. Given at least one physical resource block (PRB) is assigned to a node for transmission, the data rate for each node is achieved by the following equation:

$$S_{(nr)} = \frac{\sum_{p=1}^{R} (\chi^{nr}) \cdot (\zeta) \cdot (M) \cdot (r^{nr})}{T_{slot,ms}} \tag{2}$$

(2) represents the theoretical bit rates that can be achieved on 5G NR transmission. χ^{nr} stands for the subcarriers available for transmission, ζ is the number of bits per symbol per carrier, M is the modulation order, r^{nr} is the coding rate and $T_{slot,ms}$ are the number of slots transmitted within a given channel occupancy time (COT) in milliseconds.

LBT Procedure - 5G NR-U release 16 adopts similar channel access mechanisms to LTE-LAA as a baseline in 5GHz frequency bands. After sensing the channel to be idle for a defer time $\tau_{(\delta)}$, a counter N is decremented to zero while the channel is idle. Each decrement is done every slot interval ω ($9us$). If a collision is detected by HARQ-ACK as null acknowledgement (NACK), this triggers a doubling of the CW. Channel access priority class 4 has similar CWs to 802.11ax but different maximum COT when compare with 802.11ax maximum TXOP.

III. ML-Based Spectrum Sharing Technique for Industrial Time-Sensitive Applications

In this section, we present the ML-based technique for time-sensitive applications. The aim is to facilitate proportional opportunity for transmissions across the shared spectrum from nodes conveying time-sensitive information, based on performance requirements. This will be contingent on the number of nodes contending over the channel. The data required to train the ML model are preprocessed through establishing the distribution of the idle-time over the channel. This distribution can be used to enumerate the average data-rate and delay of coexisting networks. This can further be used to determine the optimal CW as well as COT for 5G NR-U across the channel. In a private industrial network scenario, the network can be designed to fit the specific operational requirements.

A. Uniform Difference Distribution

In order to train the ML model, the distribution of the idle-time across the channel constitutes part of the data required. Given the characteristics of the uniform distribution, the number of nodes contending over the same channel has a relationship which can be expressed by the uniform difference distribution (UDD). The UDD is the distribution of the difference between the uniformly distributed variables. For example, if two nodes with back-off selection represented as X_i and X_j, select an integer via uniform distribution, the difference in the integers selected will be the idle interval between transmissions over the channel. Each node contending (irrespective of the CW size) represents a uniformly distributed random variable (RV) X_i, with $P(X_i = x) = \frac{1}{CW}$. Hence the mean and standard deviations of the UDD of these variables provide information to estimate the number of contending nodes. This is crucial for our proposed technique, because estimating the number of contending nodes is fundamental to the proposed ML technique.

$$Y = X_i - X_j - \cdots - X_n \tag{3}$$

Y is the UDD of RV X_i, X_j, ... ,X_n. The UDD was used in [12] to estimate number of nodes in coexisting multi-RATs scenarios. Furthermore, the UDD can provide information about the delay profile based on the number of nodes contending over the channel. For instance, it can provide the average delay, based on the distribution of changing CW size associated with the back-off procedure by each node whenever a collision occurs. The expected value (mean) of a uniform RV can be expressed by its probability mass function (pmf).

$$\mu = E(X_i) = \sum_{x \in CW} x f_{X_i}(x) \tag{4}$$

where X_i is the RV, x are the elements of the CW and $f_{X_i}(x)$ is the pmf of each element x. To obtain the expected value of the UDD of two uniformly distributed RVs, we have the expression as:

$$Y = X_i - X_j, \quad x \in CW \tag{5}$$

(5) represents the UDD Y when the CW is the same for two contending nodes. Considering the discrete case, the cumulative distribution function (cdf) of Y is:

$$F_Y(y) = P\{Y \le y\} = P\{X_i - X_j \le x\} \tag{6}$$

Given, the joint pmf of the two RVs is $f_{X_i X_j}(x_i x_j)$. Where x_i and x_j have the same support S_{X_n} when contending in the same CW. Hence, the cdf of Y can be obtained as:

$$F_Y(y) = P\{Y \le y\} = P\{X_i - X_j \le y\} \tag{7}$$

We can rewrite (7) as $P\{X_i \le Y + X_j\}$. $F_Y(y)$ is computed as:

$$\sum_{0}^{x_j} \sum_{0}^{Y+X_j} f_{X_i X_j}(x_i, x_j). \tag{8}$$

In order to obtain the pmf of the distribution we obtain the derivative of the cdf which is:

$$\frac{\mathrm{d}}{\mathrm{d}y} F_Y(y) = \sum_{0}^{x_j} \frac{\mathrm{d}}{\mathrm{d}y} \sum_{0}^{Y+X_j} f_{X_i X_j}(x_i, x_j) \tag{9}$$

When X_i and X_j are independent, which is the case in our model we have the pmf $f_Y(y)$ as:

$$\sum_{0}^{x_j} f_{X_i}(Y + X_j) f_{X_j}(x_j) \tag{10}$$

(10) is the convolution of the pmf of both RVs X_i & X_j. To obtain the uniform difference distribution for three nodes, the convolution of the pmf of Y and X_k will apply, and so on as the number of nodes increases. The mean of the uniform difference distribution is therefore:

$$\mu = E(Y) = \sum_{x \in X_i - X_j} x f_Y(x) \tag{11}$$

In a more realistic scenario where nodes contending for the channel operate across different CWs due to collision, the binary exponential sequence follows $2^s CW$ where $s \in \{0, 1, 2, ...6\}$ the backoff stage.

$$f^s_{x_i} = P(X_i = x) = \frac{1}{2^s CW_s} \tag{12}$$

Equation (12) shows the pmf subject to the backoff stage experienced by a node. The expected value and the cdf of a node contending within a specific CW (represented as a RV) can be similarly written as:

$$E^s(X_i) = \sum_{x \in CW_s} x f^s_{x_i}(x) \tag{13}$$

$$F^s_{X_i}(x) = P(X_i \le x), \qquad 0 \le x \le CW_s - 1 \tag{14}$$

The uniform difference distribution of two uniform RVs where X^s_i and X^s_j have a joint pmf as $f_{X^s_i X^s_j (x_i x_j)}$ with different support.

The cdf of the uniform difference distribution denoted as Y is given as:

$$F_Y(y) = P\{Y \le y\} = P\{X^s_i - X^s_j \le y\} \tag{15}$$

Rewriting (15) we have $P\{X^s_i \le y + X^s_j\}$. The cdf $F_Y(y)$ is then computed as:

$$\sum_{0}^{x_j} \sum_{0}^{Y+X^s_j} f_{X^s_i X^s_j}(x_i x_j) \tag{16}$$

When the derivative is obtained for (16), the expected values of the uniform difference distribution is:

$$E(Y) = \sum_{y \in CW_m} y \frac{\mathrm{d}}{\mathrm{d}y} F_Y(y) \tag{17}$$

$E(Y)$ and standard deviation (σ_Y) of the UDD constitute the data required for the node number N_T estimation and computing the mean individual node data-rates and delay.

B. Spectrum Sharing Algorithm

The spectrum sharing technique is designed to offer priority transmission opportunity based on transmission activity data obtained from the system model described above. The algorithm is given below in Algorithm 1.

Algorithm 1 Spectrum Sharing Technique

Initialize idle-time interval counter to zeroes
Begin idle-time counting through channel sensing
Compute $E(Y)$ and σ_Y of idle-time distribution Y
Get the total node numbers N_T from $E(Y)$ and σ_Y
Define S^i_{nr}, S^i_w per node for 5G and 802.11ax data-rates
Define D^i_{nr}, D^i_w per node for 5G and 802.11ax delay
for Time $t = 1, \ldots, \infty$ **do**
  while N_T is not zero **do**
    $S^i_{nr} \leftarrow$ Data-rate for N^i_{nr}
    $S^i_w \leftarrow$ Data-rate for N^i_w
    if $S^i_{nr}, D^i_{nr} \ll App_{N_T}$ **then**
      $CW \leftarrow$ ML Optimal CW Prediction
    else if $S^i_{nr}, D^i_{nr} \ge App_{N_T}$ **then**
      $CW \leftarrow$ 5G NR-U LBT Procedure
    end if
  end while
end for=0

C. Dataset

The dataset used to train the ML models for numerical analysis and evaluating the ML performance were generated with MATLAB. In order to extract the idle-time interval between transmissions, a MAC layer channel contention model was developed in MATLAB for 5G NR-U and 802.11ax coexisting scenarios. As shown in the algorithm above, the idle-time interval provides the dataset to estimate the number of nodes. The idle-time interval and COT/TXOP also enable computing the mean data-rates and delay for each node using the PHY model. This was done for a set of carefully selected CW sizes for 5G NR-U nodes to choose from, to minimize transmission collision and achieve optimal data-rates and delay.

D. ML Models

Various ML models are employed in this study based on their effectiveness in spectrum-sharing applications. Support Vector Machine (SVM) is utilized due to its ability to handle non-linear decision boundaries, making it suitable for industrial settings where spectrum usage patterns may not be linearly separable. Linear Discriminant Analysis (LDA) is chosen for its capacity to simplify classification by projecting data onto a lower-dimensional space with well-separated classes, particularly useful in complex industrial environments. K-Nearest Neighbors (KNN) is applied for its flexibility and adaptability, providing localized spectrum allocation decisions based on neighbouring devices' usage patterns, especially in dynamic industrial settings. Random Forest (RF) is relied upon for its reliability in dynamic industrial environments, robustness against overfitting, and capability to manage large volumes of data with high dimensionality. Decision Trees (DT) are preferred for their simplicity and transparency, offering insights into spectrum allocation decisions in industrial settings and adaptability to various spectrum consumption features. Artificial Neural Networks (ANN) can efficiently learn and adapt to complicated radio frequency data patterns, improving spectrum efficiency and resource allocation in dynamic wireless environments. In addition, lightGBM (LGBM) is considered for its efficiency and high performance in handling large datasets with complex features, enhancing the spectrum-sharing analysis in this study.

IV. Results

The result of this study is presented in this section covering ML model and system performance.

A. Spectrum Sharing

Several machine learning algorithms were evaluated for their performance in classifying the optimal CW to enable optimal performance in achieving better video compression bitrate for better object detection. The results, as outlined in Table I, shed light on the strengths and weaknesses of each algorithm. SVM and RF exhibit the highest classification accuracies, both achieving a significant rate of 92%. In sectors characterized by stringent temporal constraints such as

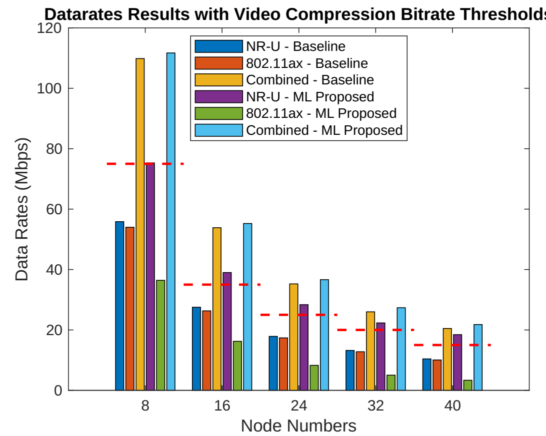

Fig. 2. Data-rates results with video compression bitrate thresholds showing performance of baseline and proposed ML-Technique

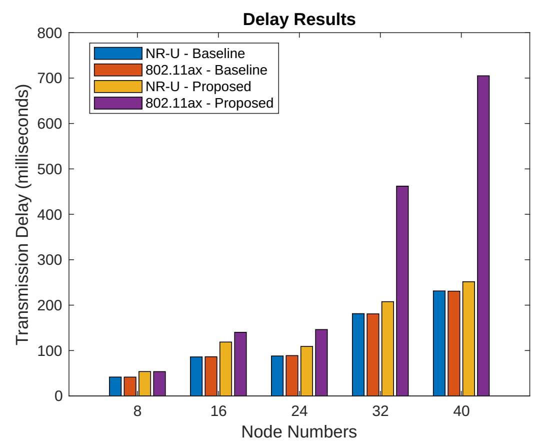

Fig. 3. Transmission delay results showing baseline and proposed ML technique performance

industrial environments, precision assumes paramount importance to ensure optimal allocation and utilization of spectrum resources for mission-critical operations. KNN and LDA attain slightly lower accuracies, at 86% and 80% respectively, owing to the inherent complexity of the data they encounter. Nonetheless, their proficiency in discerning intricate patterns within non-linearly separable datasets endows them with the ability to effectively classify instances based on their feature representations. This adaptability to diverse data distributions renders them particularly adept at reliably categorizing time-sensitive data amidst the multifaceted and dynamic spectrum environments prevalent in industrial settings. DT, ANN, and LGBM achieve accuracies hovering around the 90% mark, positioning them slightly below SVM and RF in performance but ahead of LDA and KNN.

However accuracy could be insufficient to fully capture the performance demands of time-sensitive applications. Recall, F1 score, precision, and other metrics are important indicators of the effectiveness that classifies positive cases while reducing false positives and false negatives. RF, SVM and ANN perform well in these parameters, achieving a precision of 97%, 94%

TABLE I
ML RESULTS OF THE SPECTRUM SHARING TECHNIQUE FOR TIME-SENSITIVE APPLICATIONS IN INDUSTRIAL SCENARIOS.

Alg.	Accuracy	Precision	Recall	F1score	time (sec)
SVM	**92%**	**94%**	**92%**	**93%**	**0.002061367034**
LDA	80%	82%	80%	78%	0.002042770385
KNN	86%	81%	82%	80%	0.12220454216
RF	**92%**	**97%**	**92%**	**93%**	**0.39560770988**
DT	90%	93%	90%	91%	0.00201344490
ANN	90%	93%	90%	91%	0.18818640708
LGBM	89%	91%	89%	89%	0.7498244312

and 93%, recall of 92%, 92% and 90%, and F1 score of 93%, 93% and 91%, respectively. Recall ensures that all relevant cases are correctly identified, while precision takes on greater importance in time-sensitive industrial scenarios, guaranteeing that the proportion of spectrum resources are properly utilized for vital activities. RF's performance in terms of precision, recall, and F1 score is in close accordance with the requirements of industrial applications that require quick selection. Furthermore, the efficacy of real-time spectrum sharing in industrial scenarios, where prompt decision-making is imperative, hinges on the computational efficiency of the algorithms employed. SVM, with a training time of 0.002 seconds, and RF, with a training time of 0.396 seconds, emerge as apt choices for applications necessitating rapid spectrum sharing decisions. Their effectiveness in high-dimensional spaces facilitates prompt adaptation to dynamic spectrum environments prevalent in industrial settings, where spectrum conditions may undergo rapid changes, ensuring the seamless operation of time-sensitive applications. Conversely, DT demonstrates a longer processing time at 0.021 seconds. The complexity inherent in DT may account for this increased computational overhead, albeit without imparting significant differences for systems with lower computational demands.

B. System Performance

A comparative evaluation of both RATs is carried out to ascertain the performance of the proposed spectrum sharing approach over the 802.11ax and 5G NR-U standard. The philosophy behind the approach in industrial scenarios aims to facilitate proportionate and application-driven spectrum sharing in a pragmatic way. In Fig. 2, the data-rates results of the proposed technique consistently improves the video compression bitrate above the threshold for 5G NR-U network through which the video traffic for material sorting is transmitted. This performance is crucial to improve the AP for object detection tasks. For 8 nodes, an average data-rate improvement from 55.84 Mbps to 75.27 Mbps is attained improving the video compression bitrate by 36%. Consequently, the 802.11ax network experiences a reduction in data-rates from an average of 53.98 Mbps to 36.42 Mbps. This is a nominal reduction and is able to adequately support system monitoring applications on digital dashboards. This trend is sustained to 40 nodes where an impressive video compression bitrate of 18.44 Mbps is achieved from a baseline of 10.41Mbps. Equally interesting is the slight improvement in combined data-rates of 5G NR-U and 802.11ax from 109.83 Mbps to 111.69 Mbps for 8 nodes and from 20.4 Mbps to 21.77 Mbps for 40 nodes. This reveals, a balance can be achieved with the CW to offer proportionate contention without degrading the spectral utilization over the channel. In Fig. 3, the transmission delay similarly maintains good performance to 24 nodes at $< 150ms$. However, 802.11ax delay increases as the number of nodes increase substantially. Its important to note with substantial number of nodes contending over the channel, a good balance between spectral efficiency and transmission delay must be determined.

V. CONCLUSION

In this paper, a ML-based technique is proposed applying the UDD to establish the distribution of the idle-time interval. This enables computing the data-rates and delay of both 5G NR-U and 802.11ax nodes. Furthermore, it enables obtaining the optimal CW to improve data-rates proportionately to networks supporting critical operations but also improving system performance for critical industrial applications.

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