On the Impact of TIG Welding Interference on Industrial Wi-Fi Networks: Modeling of Empirical Data and Analytical Studying of Coexistence

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***Abstract*—The use of IEEE 802.11 Wi-Fi in industrial applications has been enabled by time-sensitive networking (TSN) capabilities to achieve deterministic communications within time-critical applications. However, the medium access control (MAC) layer of the IEEE 802.11 still performs a carrier sense multiple access (CSMA) scheme to access the shared medium. As a result, any wireless interference over the shared medium can impact the performance of IEEE 802.11 industrial wireless networks through collisions or occupying the medium leading to increased latency and decreased service quality. By measuring the electromagnetic signal behavior of Tungsten Inert Gas (TIG) welding, we have found that it can cause interference at the 2.4 GHz band, commonly used by the IEEE 802.11 networks. In this work, we first model the measured TIG welding signal as a partitioned Markov chain, where its structure and transition probabilities are derived to accurately represent the TIG welding behavior. Then, we utilize the Markov chain model of IEEE 802.11 by Bianchi and its derivatives to predict the throughput of the IEEE 802.11 networks with TIG welding interference.**

***Index Terms*—Industrial wireless, interference modeling, TIG welding, Wi-Fi, wireless systems**

I. INTRODUCTION

The use of wireless communications technologies for industrial applications is an enabler for the advanced manufacturing vision of massive connectivity, flexible manufacturing, and extended use of mobile platforms. Various wireless technologies can be deployed for different classes of devices and applications ranging from basic ambient environmental sensing and the industrial internet of things (IIoT) to time-sensitive applications, mission critical sensing, precisely timed actuation, feedback motion control, and safety integrated systems (SIS) [1]–[4]. The use of IEEE 802.11 in home and office applications is widespread and it is used for multiple industrial best-effort applications because of its random access medium access control (MAC) in its current widely-used versions such as 802.11ac [5], [6]. Furthermore, the use of time sensitive networking capabilities over IEEE 802.11 networks allowed their deployment for time-critical applications as well.

In IEEE 802.11 Wi-Fi networks, stations are able to send packets when the medium is available through a carrier sense multiple access (CSMA) scheme. The stations also employ energy detection to be able to detect any activity on a specific channel from either other IEEE 802.11 stations or non-IEEE 802.11 sources. When an activity is detected, a station runs a back-off timer to wait for a random period before performing another transmission attempt. Packets can be dropped after a specific number of back-offs. On the other hand, if a collision happens due to an interference source that becomes active while a packet is being transmitted, the packet may be lost or corrected using forward error correction (FEC). Hence, retransmission of the corrupted packets may be needed. As a result, interference can cause delays and packet loss in IEEE 802.11 networks which is more crucial for time-critical industrial applications [7].

In industrial environments and in addition to interference resulting from various communications networks, industrial equipment can also produce electromagnetic over-the-air (OTA) signals that can occupy the radio spectrum. As an example, we measured the OTA activity from a Tungsten Inert Gas (TIG) welding station and found that it produces interference in the 2.4 GHz band. The measurements were taken in the machine shop of the National Institute of Standards and Technology (NIST), in Gaithersburg, Maryland. In order to study the impacts of the TIG welding interference and other non-communications interference signals, the measured data needs to be statistically modeled and characterized. The resulting models can be either analytically integrated into existing IEEE 802.11 models or used to recreate interference signals in a controlled environment, where IEEE 802.11 networks are deployed.

The measured TIG welding signal was found to be composed of a number of irregular pulses that are not periodic. The burstiness of the TIG welding activity in the 2.4 GHz band is similar to the behavior of many other natural and human-made systems, examples being in communications and computer networks. In order to understand the characteristics and properties of this stream of bursts, time-domain statistical modeling is needed, where the results can be used for modeling and recreation of the measured data. Markov chains have been widely used for modeling random correlated events including simple impulsive noise streams [8]. However, in order to capture the minimum run time of a signal, a partitioned Markov chain is used [9].

In this work, we start by analyzing the empirical TIG welding measurements to capture the features needed for the partitioned Markov chain model. We also perform a number of pre-processing stages on the measured data such as resampling and quantization, to match the time resolution of the IEEE 802.11 network model and to effectively model the TIG welding signal using a Markov chain. Furthermore, we explain the detailed steps for building the Markov model by defining its various parameters, including the minimum and maximum activity run times and the transition probabilities between its different states. Finally, we integrate the output of the Markov chain model to the Bianchi IEEE 802.11 model [10] to see the impact of the TIG welding interference on the wireless network performance, including the throughput of the network.

II. Interference Data Modeling

In this section, we briefly discuss the measured TIG welding interference characteristics and data collection setup. Then, we discuss the selected partitioned Markov chain model and its defining parameters. Finally, we explain the complete modeling process, including the data preparation stage and the partitioned Markov model parameters evaluation from the measured data.

A. Measurement Data

As an example of non-communications interference, we consider TIG welding electromagnetic emissions in the 2.4 GHz band. The welding machine used is the Miller Syncrowave 350LX, which is set up for applying AC current of 200 Amperes. It was used to weld an aluminum plate with supplied Argon gas. To capture the corresponding electromagnetic emissions, we used a Rhode and Schwartz spectrum analyzer with 160 MHz of real-time bandwidth and a TSA900 directional ultra-wideband PCB Tapered Slot antenna with frequency range from 900 MHz to 12 GHz. The antenna was placed about 4 meters from the welding location. A photo of the welding location and the antenna is shown in Fig. 1.

The spectrum of the measured TIG welding in the 2.4 GHz band was found to be almost flat over the whole band. The time-domain signal was found to be formed as a pulse train where random idle periods existed, as shown in Fig. 2. Moreover, the pulses were not uniform and were mainly composed of impulses of different powers including smaller idle periods within the pulses. The measurements are sampled at a rate of 625 Msamples/second. The temporal variation of the measured TIG welding signal can be characterized by the idle periods distribution including the minimum and maximum idle periods, and the impulses distribution including the correlation between various power levels and the minimum and maximum pulse widths.

B. Partitioned Markov Chain

In order to evaluate the impact of TIG welding on the communication activities on the 2.4 GHz band, a concise model of the temporal behavior is needed. A stochastic model is required because of the random bursts and impulses in the TIG welding signal. A Markov chain is generally used to model correlated discrete events or correlated samples in a stochastic signal. However, the TIG welding signal is characterized by having periods of contiguous idle and active pulses within the signal. Each group of the idle or active pulses is characterized by a maximum and a minimum pulse width. As a result, a partitioned Markov chain is a suitable modeling tool where numbers of transition states and specific sets of grouped states exist to guarantee that the modeled Markov chain captures the pulsed behavior of the TIG welding signal.

The proposed Markov chain requires power to be discretized into N levels, plus one additional power level when idle. These

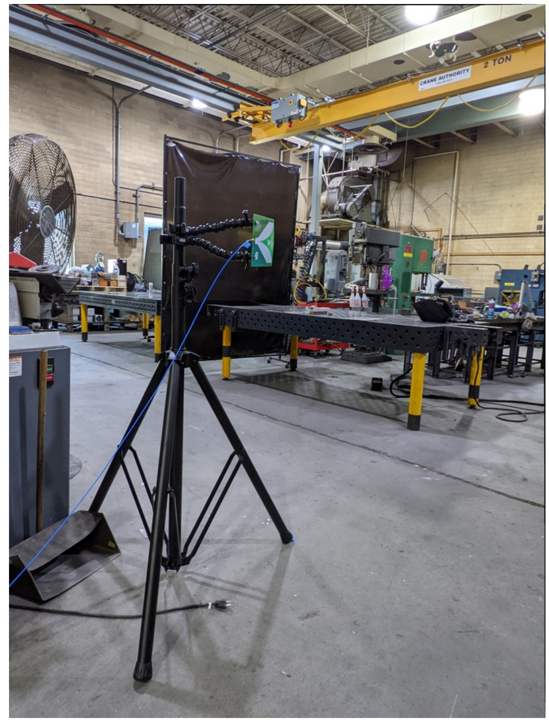

Fig. 1. The NIST machine shop welding station and measurent antenna

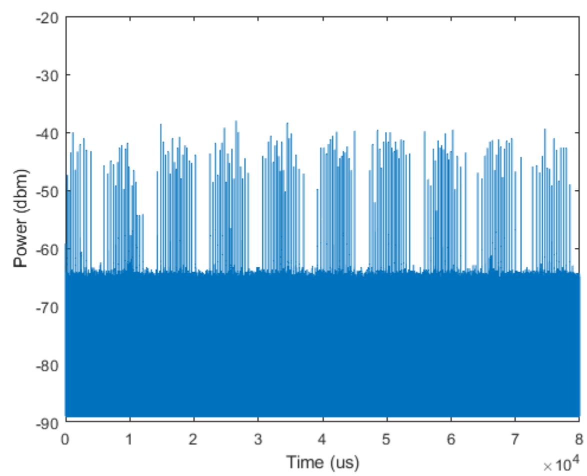

Fig. 2. Example of the time-domain measured data

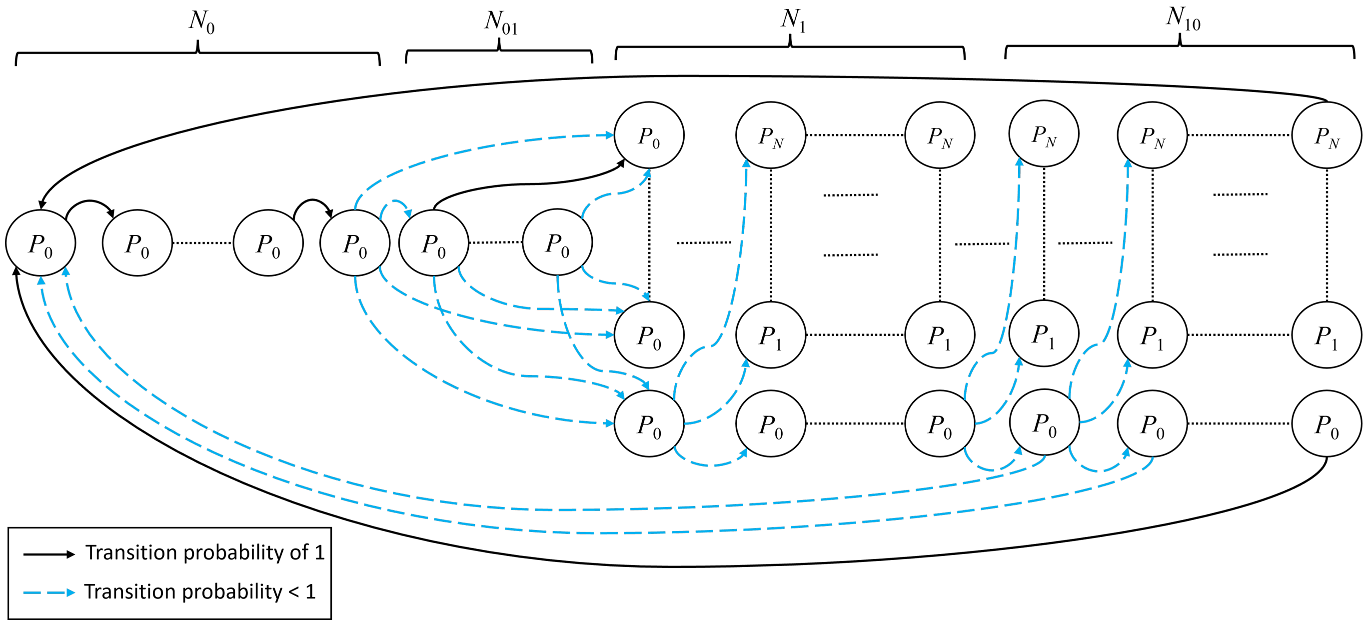

Fig. 3. Illustration of the partitioned Markov chain and its transition probabilities

power levels are denoted by P_i where $i = 0, 1, 2, ...N$. The states of the Markov chain are partitioned into four different partitions reflecting the temporal behavior of the TIG welding signal, as shown in Fig. 3. First, we consider the partition in idle mode in which the state reflects a power level of P_0 and transition to another idle state with probability 1. The length of this partition is N_0 which reflects the minimum number of idle states in the Markov chain. Second, we consider the partition in idle mode at which the Markov chain can move to the active state with some probability. The power level of the states in this partition is P_0, as well and the length of this partition is N_{01} which reflects the difference between the maximum and the minimum number of idle states that can exist.

The other two partitions reflect the statuses of the active states. The third partition contains the states when active with any power level, but cannot transit to the first idle partition. It contains $N_1 \times (N + 1)$ states and the value N_1 that reflects the minimum number of states while continuously being active. The last partition contains the active states that can transit directly back to the first idle partition. It contains $N_{10} \times (N + 1)$ states and the value N_{10} reflects the difference between the maximum and the minimum number of states while continuously active.

C. Interference Data Modeling Process

In this subsection, we discuss the process used for modeling the collected TIG welding measurements into the proposed partitioned Markov chain. The block diagram of the proposed process is shown in Fig. 4. The first stage is the measurement collection of the temporal behavior of the TIG welding interference. This time domain signal of the I/Q received power can be captured directly or evaluated from a spectrum capture of the data. The sampling rate of the measured data has to be high enough to allow the integration with the Wi-Fi model to study the TIG welding impact. We will discuss the sampling rate requirements for the Wi-Fi model in the following section.

The following stage is to threshold the signal at the noise floor. Keeping signals that are below the noise floor will negatively impact the evaluated resampled values. Any sample value below the noise floor has a superficial value, and hence, it is replaced by the noise floor value. The following phase is deploying a rolling average resampling to have the measured signal sampling frequency match the impacted network sampling frequency. Due to the impulsive nature of the measured signal, a rolling-average resampling is needed to maintain the average power impact on the Wi-Fi network.

Quantization is needed to build the Markov chain using the assigned discrete power levels. Generally, selecting the number of quantization levels and deciding whether to use uniform or non-uniform quantization techniques can be optimized while considering the trade-off between minimizing the quantization loss and keeping the computational complexity feasible. In this work, we consider the case of uniform quantization.

The last stage is the evaluation of Markov chain parameters from the measured data. First, we evaluate the minimum and maximum numbers of idle-state samples through all the measured data, and these numbers define the values of N_0 and $N_0 + N_{01}$, respectively. Then, we evaluate the minimum and the maximum numbers of pulsed samples through all the measured data and these numbers define the values of N_1 and $N_1 + N_{10}$, respectively. Second, we evaluate the transition probabilities between various states of the Markov chain. The transition probabilities are evaluated numerically from the measurements. The transition probability from a pair

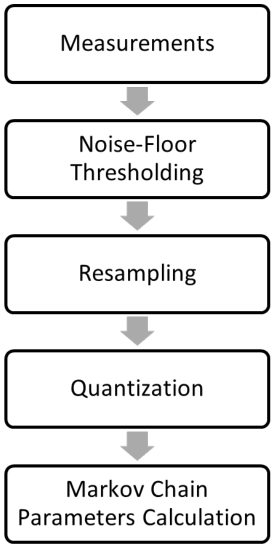

Fig. 4. Block diagram of the interference data modeling process

of states is evaluated by dividing the number transitions from the origin state to the destination state by the number of all the transitions from the origin state.

The first set of transition probabilities are the ones from the states in the second partition going from one idle state either to the next idle state or to one of the states in the first sample of the pulsed states. These transition probabilities are denoted by $p_{\mathrm{I}-x}$, where $x \in \{\mathrm{I}, P_0, P_1, ...P_N\}$ and I denotes an idle state. The following set of transitions probabilities are for the states of the third partition which are denoted by p_{y-z}, where y and z are $\in \{P_0, P_1, ...P_N\}$. The transition probabilities for the fourth partition, except for the last sample, are defined by p_{u-v}, where $u \in \{P_0, P_1, ...P_N\}$ and $v \in \{\mathrm{I}, P_0, P_1, ...P_N\}$. The states of the last sample in the Markov chain has $p_{w-\mathrm{I}} = 1$, where $w \in \{P_0, P_1, ...P_N\}$.

III. Interference Impact on Industrial Wi-Fi Networks

In this paper, we use the analytical model presented in [11] to derive the IEEE 802.11 Wi-Fi network performance. That work models the MAC layer of IEEE 802.11 with CSMA/CA, and studies how neighboring nodes and non-IEEE 802.11 interfering sources impact the wireless network performance. The work is based on a refinement [12] of Bianchi's characterization of IEEE 802.11 [10]. The key point is that [11] extends the underlying Markov chain to also capture the presence of an interference source that is active for a period of T_{if} transmission slots and emits with a probability p_{if}. The proposed model also captures both the back-off mechanisms and re-transmissions (RTX) of frames upon collision in the IEEE 802.11 wireless links.

In our model, the value of the probability p_{if} is evaluated as the sum of the steady state probabilities of the states where the power level is detected by the Wi-Fi network. The value of T_{if} is also calculated from the Markov chain as the average number of samples that the interference power level remains above the detection threshold of the Wi-Fi network. The aforementioned model, in [11], obtains the steady-state probability of each state, in particular, it derives the probability that a frame has to be transmitted again after j unsuccessful re-transmissions, denoted as a_j.

Three parameters were defined for the Wi-Fi Markov chain that will be used to evaluate the performance metrics. The parameter p is the probability that the transmission of a packet is not successful. The probability τ is the probability that a station starts sending a packet in a randomly chosen time slot. Finally, the parameter ω is the probability that during an ongoing packet transmission, the interference source becomes active, but does not lead to the loss of a packet. The value of ω depends on the FEC mechanism used. The two governing equations for the probabilities are as follows:

$$\tau = \frac{b(0,0) \cdot (1 - p^{m+2})}{1 - p} \tag{1}$$

$$p = 1 - (1-\tau)^{n-1}[(1-p_{if})^k + (1 - (1-p_{if})^k) \cdot \omega] \tag{2}$$

where $b(0,0)$ is the steady state probability of being in the first back-off state, $m+2$ is the number of the back-off stages in [11], n is the number of Wi-Fi stations, and k is the number of time slots for a packet transmission.

In this work, we will use the throughput as the performance metric to study the impact of welding on Wi-Fi transmissions. However, other metrics can be measured, such as latency and error rate which will depend on the Wi-Fi station traffic model. The throughput was evaluated, at [11], as follows:

$$U = P_{\mathrm{B}}\tau(1-\tau)^{n-1}(1-q) \cdot \frac{((1-p_{if})^{k+1} + \omega(1-(1-p_{if})^{k+1}))}{\tilde{\sigma}} \tag{3}$$

where P_{B} is the packet length in bytes and $\tilde{\sigma}$ is the average channel slot time.

IV. Results

In this section, we present the results of using the TIG welding Markov chain model to evaluate the interference probability that impacts the Wi-Fi network throughput. We start by discussing the TIG welding measurements processing results. Then, we discuss the Wi-Fi network throughput results.

A. TIG Welding Measurements Processing

In Fig. 5, we show the resampled version of the original measurements where the new sampling period is 1 ms to match the time slot of the IEEE 802.11 system under study. A noise floor threshold of -64 dBm is used. The lower values of the resampled signal is because of the lower average power compared to high instantaneous power in specific impulses in the measured signal. The resulted signal is used to tune the parameters of the partitioned Markov chain that can be used to produce a stream of samples with similar stochastic characteristics or evaluate the interference probability, in this case, impacting the Wi-Fi communications network.

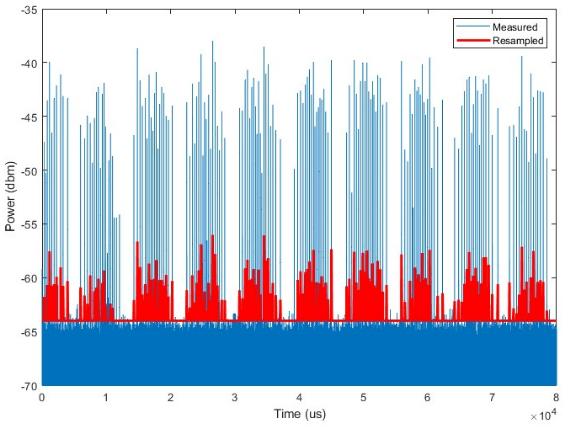

Fig. 5. The resampled version of the measured data.

B. Throughput of a Wi-Fi network impacted by TIG welding Interference

The Wi-Fi network is assumed to have a bit rate of 54 Mbps, a packet size of 1530 bytes, a system slot of 1 ms, a propagation latency of 9 ms, and a minimal back-off window size of 32. A transmission is successful if only one Wi-Fi station transmits and the interference does not lead to packet loss due to the presence of the FEC mechanism. In the following result, we present the throughput values considering the interference being active at either -60 or -64 dBm.

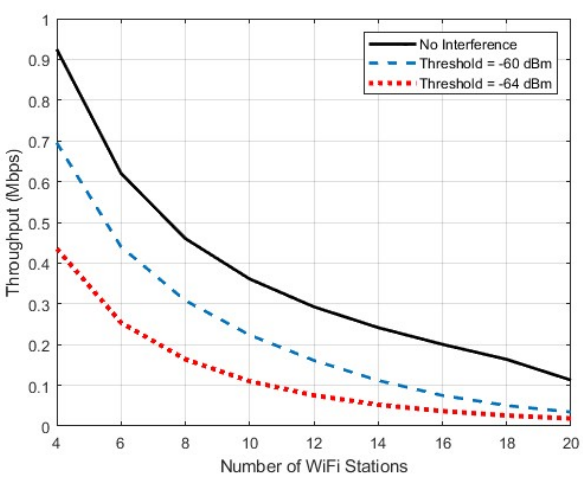

Fig. 6. The throughput of the WiFi network against the number of nodes in the system impacted by the TIG welding interference.

In Fig. 6, the degradation in the Wi-Fi network throughput is presented against the number of stations when the measured TIG welding interference is applied. The existence of TIG welding with -60 dBm threshold has an impact of almost four additional stations in the Wi-Fi network. In this case, the FEC recovery probability is fixed at 0.1. Moreover, the difference between the TIG welding impact curves at different thresholds demonstrate the impact of interference power loss in the performance degradation where a 4 dB difference in the interference signal can have a significant impact on the WiFi network.

Finally, in Fig. 7, we demonstrate the impact of the FEC recovery probability on a Wi-Fi network that is impacted by the interference caused by TIG welding. The TIG welding interference is stochastic, hence it does not cause any structured interference on the Wi-Fi network so linear curves resulted with a higher slope at the higher interference value.

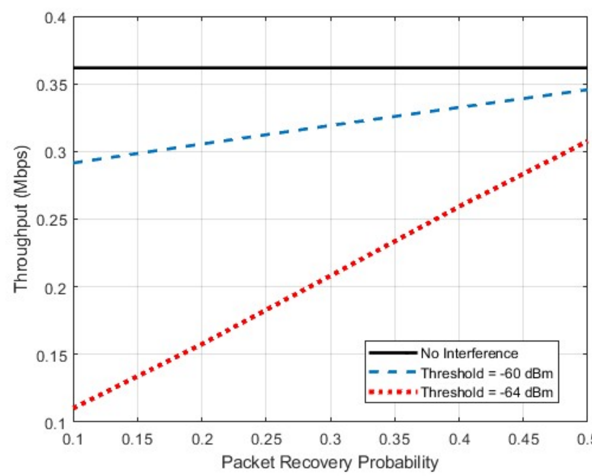

Fig. 7. The throughput of the WiFi network against the WiFi FEC factor impacted by the TIG welding interference.

V. Conclusions

In this article, we presented a modeling procedure for non-communications industrial wireless interference in order to recreate the signal in a lab environment and analytically study its impact on operational industrial wireless communications systems. The modeling procedure deployed a partitioned Markov chain, which allows satisfying a minimum and maximum run time of the idle and pulsed periods of the interference data. The procedure is applied on a measured TIG welding signal and its performance is assessed. Further, the steady-state probabilities of the Markov chain was used to analytically study its impact on Wi-Fi wireless systems.

This procedure can be further deployed and implemented through the emerging IEEE P3388 [13] standard testing procedures. The proposed IEEE P3388 provides a reference test architecture for the performance evaluation of industrial wireless systems and an assessment process for various industrial wireless use cases. In this paper, an example of TIG welding modeling process is introduced and can play a crucial role in the deployment of the standard where aggressor recreation is needed. Furthermore, the TIG welding measurements modeling process can be used for various pulsed industrial wireless electromagnetic aggressors.

Disclaimer Certain commercial equipment, instruments, or materials are identified in this paper in order to specify the experimental procedure adequately. Such identification is not intended to imply recommendation or endorsement by the National Institute of Standards and Technology, nor is it intended to imply that the materials or equipment identified are necessarily the best available for the purpose.

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