Implementation of Efficient Real-Time Industrial Wireless Interference Identification Algorithms with Fuzzified Neural Networks

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***Abstract*—Real-time industrial wireless systems sharing a crowded spectrum band require active coexistence management measures. Identification of wireless interference is a key issue for this purpose.**

We propose an efficient implementation of a wireless interference identification (WII) approach called neuro-fuzzy signal classifier (NFSC). The implementation in Matlab / SIMULINK is based upon the wideband software defined radio Ettus USRP N210. The implementation is evaluated in six selected heterogeneous and harsh industrial scenarios within the license-free 2.4-GHz-ISM radio band with variously combined standard wireless technologies IEEE 802.11g-based WLAN and Bluetooth. The evaluation of the NFSC was performed with a binary classification test with the statistical measurement metrics sensitivity and specificity.

I. Introduction

License-free spectrum bands such as the 2.4-GHz-ISM band are shared between incompatible heterogeneous wireless communication systems. In industrial environments, typically standardized wireless communication systems within the 2.4-GHz-ISM band are wide-band high-rate IEEE 802.11 b/g/n, narrow-band low-rate IEEE 802.15.4-based WirelessHART and ISA 100.11a, and IEEE 802.15.1-related PNO WSAN-FA and Bluetooth. Additionally, the spectrum band is shared with many proprietary wireless technologies which target specific application requirements such as the IEEE 802.11-based industrial WLAN (iWLAN) from Siemens AG, FHSS-based Trusted Wireless from Phoenix Contact and IEEE 802.15.1-based WISA from ABB Group.

Any radio-frequency interference can cause packet loss and transmission latency for industrial radio communication systems. Both effects have to be mitigated for real-time medium requirements. Therefore, the norm IEC 62657-2 [1] for industrial radio communication systems recommends an active coexistence management for reliable medium utilization. They recommend (i) manual, (ii) automatic non-cooperative or (iii) automatic cooperative coexistence management. The first approach is the most in-efficient one, due to time-consuming complex configuration effort. The automatic approaches (ii) and (iii) enable efficient self-reconfiguration without manual intervention and radio-specific expertise. An automatic cooperative coexistence management (iii) requires a control channel, i.e. a logical common communication connection between each coexisting wireless system to enable deterministic medium access. In case of a single legacy coexisting wireless system without such connection, the non-cooperative approach (ii) is recommended. Non-cooperative coexistence management approaches are aware of coexisting wireless systems based on independent wireless interference identification (WII) and mitigation.

The requirement of WII relates to the well-known research field of specific emitter identification (SEI) [2] which is also called physical layer identification [3]. In contrast to SEI, WII targets the identification of multiple wireless technologies sharing the same spectrum band. So, the approaches have to be independent of wireless technology specific characteristics such as modulation, spreading technique, coding, or data. Further, WII suffers from limited knowledge of the identified wireless technologies. While many radio systems are based upon a-priori known standardized wireless technologies such as IEEE 802.11, IEEE 802.15.1 and IEEE 802.15.4, some utilize application-specific modulation, spreading technique or coding approaches. Therefore, modulation-based SEI approaches such as proposed by Brik et. al. [4] are not practicable. Advantageous are technology-independent waveform-based SEI approaches such as the FFT-based turn-on transient analysis approach proposed by Danev et. al. [5].

In this paper, we propose an efficient implementation of a WII approach for industrial wireless environments based on fuzzified neural networks [6].

The paper is structured as follows. The subsequent section II introduces the WII approach called neuro-fuzzy signal classifier (NFSC). Section III discusses the results of extensive evaluation. The final section IV concludes this paper.

II. Fuzzified Neural Network based Wireless Interference Identification

A signal classification process usually consists of several cascaded layers. The input signal $x(t)$ is in general a superposition of the desired signal, various other unknown signals, and noise. Prominent signal features are extracted from this

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superposition, such as symbol rate, modulation, bandwidth etc., and used next as distinct features for the signal classifier. The classifier assigns input signals to different classes, here primary user (PU) signal labeling, depending on the extracted information from the features.

A NFSC was proposed, which utilizes a-priori known signal features to classify PU systems by utilizing fuzzy logic based rules [7]. The utilized distinct features are: (i) Center frequency, (ii) bandwidth, (iii) pulse shape, (iv) time behavior and (v) hop behavior of PU systems.

The NFSC consists of six layered neural network as shown in Figure 1. A neural network comprises process elements, or neurons, which are interconnected to form a computation network. The functionality of each layer will be discussed in the following sections of this section. Input and fuzzification layer

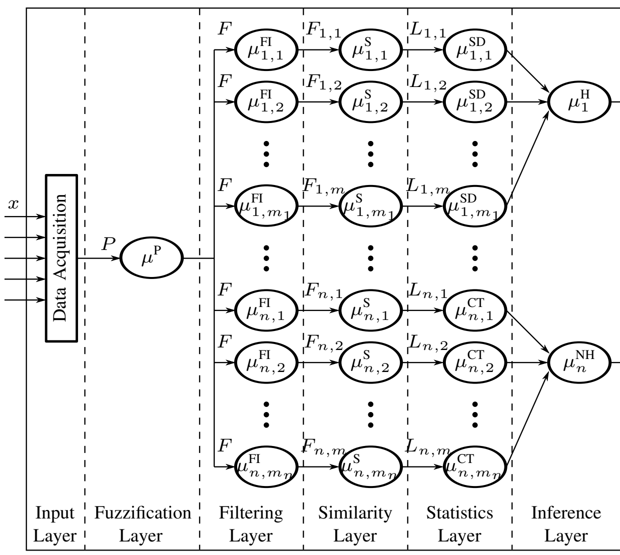

Fig. 1: Block diagram of the NFSC (adapted from [7])

consist of only one process element each. The inference layer consists of two process elements for each PU system, thus for n PU systems there are $2n$ process elements in this layer. There is exactly one process element corresponding to each channel of each PU system in all other layers. Consequently, if m_i denotes the total number of frequency channels of the i^{th} PU system, then each of these layers contains $\sum_{i=1}^{n} m_i$ process elements.

A. Input Layer

In the first layer, a discrete logarithmic power spectrum density (PSD) is computed from the acquired discrete complex input signal. The discrete complex input signal represents in-phase and quadrature values. In general, from a discrete input signal $x[n]$ its continuous Fourier transform $X(\omega)$ is $x[n] \circ\!\!-\!\!\bullet X(\omega)$. However, the practical implementation of the discrete Fourier transform on a computer nearly always uses the fast Fourier transform (FFT) algorithm. In this paper, the FFT algorithm with some additional computations is applied to compute the desired discrete logarithmic PSD $P[k]$:

$$X(\omega) \mapsto P[k] \tag{1}$$

The computation of the discrete logarithmic PSD $P[k]$ is performed in a frame-based manner, depending on the selected FFT length $2^m, m \in \mathbb{N}$. A rectangular window function is applied to the discrete input signal $x[n]$, that divides the input signal into 2^m samples-length non-overlapping frames. Subsequently, the discrete PSD of each frame is computed. Note, the iterator variable n describes discrete points in time, whereas k describes discrete frequency points in the spectral range. The finite set K of all discrete frequency points k is:

$$K = \{0, 1, \dots, 2^m - 1\} \tag{2}$$

and their corresponding discrete frequencies are described by the finite set of frequencies F^{K}:

$$F^{\mathrm{K}} = f^0 + \Delta f \cdot \{-2^{m-1} - 1, -2^{m-1}, \dots, 2^{m-1}\} \tag{3}$$

where f^0 is the selected center frequency and Δf is the frequency resolution of the PSD. Δf is the ratio of the bandwidth of the input signal, called display bandwidth B^{DI}, and the selected FFT length $\Delta f = B^{\mathrm{DI}}/(2^m - 1)$. Since this paper focuses on classifying PU systems in the 80 MHz wide 2.4-GHz-ISM radio band, all elements of the frequency set F^{K} lie within the continuous ISM radio band frequency interval $f^{\mathrm{ISM}} = [2400, 2480]\,\mathrm{MHz}$.

B. Fuzzification Layer

In the second layer, the incoming PSD frame is fuzzified by utilizing a specific membership function. More precisely, with the membership function $\mu^{\mathrm{P}}[P[k]]$ the incoming PSD frame $P[k]$ is mapped to a membership value between zero and one:

$$\mu^{\mathrm{P}}[P[k]] : U_P \to [0, 1], P[k] \mapsto F[k] \tag{4}$$

where U_P is the universe of discourse in terms of fuzzy logic for the PSD frame $P[k]$:

$$U_P = \{P_{\min} \leq P[k] \leq P_{\max} \Big| k \in K\} \tag{5}$$

The applied specific membership function is:

$$\mu^{\mathrm{P}}[P[k]] = |(P_{\min} - P[k])/(P_{\min} - P_{\max})| \tag{6}$$

where $P_{\min}$ is the minimum and $P_{\max}$ the maximum constant of the incoming PSD frame. The resulting fuzzified PSD frame $F[P[k]]$ is a fuzzy set and can be written as:

$$F[P[k]] = \{(P[k], \mu^{\mathrm{P}}[P[k]]) \Big| P[k] \in U_P\} \tag{7}$$

It can be simplified, since $F[P[k]]$ depends on $P[k]$ and $P[k]$ itself depends on k, to:

$$F[k] = \{(k, \mu^{\mathrm{P}}[k]) \Big| k \in U_k\} \tag{8}$$

where U_k is the universe of discourse for k, which is equal to the finite set K. The membership function definition in eq. (4) can be rewritten through the simplification as:

$$\mu^{\mathrm{P}}[k] : U_k \to [0, 1], k \mapsto F[k] \tag{9}$$

The simplified fuzzified PSD frame $F[k]$ is named as fuzzified power spectrum (FPS) in this paper.

C. Filtering Layer

The third layer filters the incoming FPS based on the PU system's frequency channels by a pulse shape selection. In particular, the incoming FPS $F[k]$ filtered over the j^{th} channel of the i^{th} respective PU system is represented as:

$$\mu^{\text{FI}}_{i,j}[k] : [0,1] \rightarrow [0,1], F[k] \mapsto F_{i,j}[k] \tag{10}$$

where $\mu^{\text{FI}}_{i,j}[k]$ is a fuzzy membership function used as filter. For $\mu^{\text{FI}}_{i,j}[k]$ the pulse shape of the corresponding PU system is used, whereby in this paper the following rectangular pulse shape was applied:

$$\mu^{\text{FI}}_{i,j}[k] = \text{rect}\Big(\frac{f[k] - f^0_{i,j}}{D_i \cdot B^{\text{PU}}_i}\Big) \tag{11}$$

The rectangular pulse shapes are depending on three parameters: (i) The channel bandwidth B^{PU}_i of the i^{th} PU system; (ii) the constant D_i, which can be selected to adjust the passband width of the filter for the i^{th} PU system; and (iii) the center frequency $f^0_{i,j}$ of the j^{th} channel of the i^{th} respective PU system. Furthermore, the discrete frequency $f[k]$ is an element of the finite set of frequencies F^{K}, see eq. (3). For a better understanding of the filtering, an example with one PU system, $i = 1$, is discussed next and depicted in Figure 2. It is assumed that the PU system has two frequency channels: $j = [1, 2]$. An example FPS $F[k]$ is used as the input signal for the filtering layer, as depicted in upper Figure 2. Since only one PU system with two frequency channels is considered, two example fuzzy membership functions are sketched in center Figure 2. A rectangular pulse shape is chosen for both membership functions, whereas the first one is described by $\mu^{\text{FI}}_{1,1}[k]$ and the second one by $\mu^{\text{FI}}_{1,2}[k]$. The two resulting filtered FPSs are presented in lower Figure 2. In the first filtered FPS $F_{1,1}[k]$ is only the left side of the incoming FPS $F[k]$ present, whereas the right side of $F[k]$ is suppressed by the filter. On the other hand, the second filtered FPS $F_{1,2}[k]$ contains only a part of the right side of $F[k]$, whereas the left side of $F[k]$ is suppressed.

D. Similarity Layer

The fourth layer measures the similarity between the incoming filtered FPS and the PU system's ideal pulse shape to evaluate the presence or absence of the corresponding PU system in a specific frequency channel. More exact, the similarity is measured by comparing the incoming filtered FPS $F_{i,j}$ with the ideal pulse shape $\mu^{\text{PS}}_{i,j}[k]$ of the respective PU system to generate a similarity measure (SM) score $S_{i,j}$ for each j^{th} channel of the i^{th} respective PU system. The resulting SM score can be simply compared with a predefined threshold value to evaluate the presence or absence of the corresponding PU system. The comparison of the filtered FPS $F_{i,j}[k]$ with the ideal pulse shape $\mu^{\text{PS}}_{i,j}[k]$ is accomplished by computing the SM with the membership function $\mu^{\text{S}}_{i,j}$:

$$S_{i,j} = \mu^{\text{S}}_{i,j} = \frac{\sum_{f \in F^K} \min(F_{i,j}[k], \mu^{\text{PS}}_{i,j}[k])}{\max(\sum_{f \in F^K} F_{i,j}[k], \sum_{f \in F^K} \mu^{\text{PS}}_{i,j}[k])} \tag{12}$$

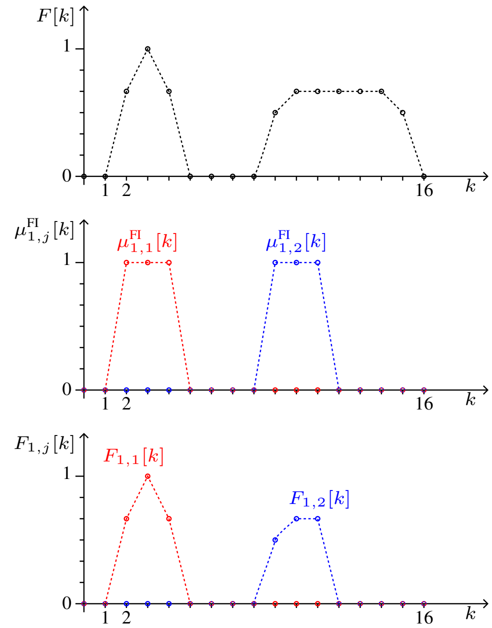

Fig. 2: Example of filtering with one PU system and two frequency channels

where $S_{i,j}$ is the measure of the presence of the i^{th} PU system in its respective j^{th} channel. In other words, with the membership function $\mu^{\text{S}}_{i,j}[k]$ the incoming filtered FPS $F_{i,j}[k]$ is mapped to a membership value between zero and one:

$$\mu^{\text{S}}_{i,j} : [0,1] \rightarrow [0,1], F_{i,j}[k] \mapsto S_{i,j} \tag{13}$$

In this paper is the same rectangular pulse shape applied for the ideal pulse shape $\mu^{\text{PS}}_{i,j}[k]$ as the one for filtering, see eq. (11), only the constant D_i is set to one, because here is the ideal pulse shape required. The resulting SM score is a fuzzy set and can be written as:

$$S_{i,j} = \{(F_{i,j}[k], \mu^{\text{S}}_{i,j}) \Big| F_{i,j}[k] \in [0,1]\} \tag{14}$$

where $S_{i,j}$ only contains one degree of membership. Elucidated, $S_{i,j}$ comprises only one single value, the degree of membership, for a specific i and j. In contrast, the fuzzy set $F_{i,j}[k]$, that contains an ordered set of fuzzy pairs $(k, \mu^{\text{P}}[k])$ for a specific i and j. Next, this single value $S_{i,j}$ is compared with a predefined threshold value γ^{S}_i for each PU system, to categorically label the presence or absence of a PU system using the membership function $\mu^{\text{L}}_{i,j}[S_{i,j}]$:

$$L_{i,j} = \mu^{\text{L}}_{i,j}[S_{i,j}] = \begin{cases} 1 & \text{if } S_{i,j} \geq \gamma^{\text{S}}_i, \\ 0 & \text{otherwise.} \end{cases} \tag{15}$$

where $L_{i,j}$ is a binary time series representing SM layer labeling. Using fuzzy set notation it can be represented as:

$$L_{i,j} = \{(S_{i,j}, \mu^{\text{L}}_{i,j}[S_{i,j}]) \Big| S_{i,j} \in [0,1]\} \tag{16}$$

Note, the label $L_{i,j}$ completely preserves frequency and time related information of an individual PU system. Hence, two very identical PU systems in terms of frequency channel definitions can not be differentiated by the labels $L_{i,j}$. Center frequencies of the frequency channels, channel bandwidth, or the quantity of the frequency channels are such channel definitions. Therefore, another feature is introduced in the following remaining two layers in order to discriminate between those PU systems.

E. Statistics Layer

In the second last layer, two statistical measures are utilized, in order to distinguish a hopping system from a non-hopping system, when two PU systems possess identical channel definitions. Descriptive statistics summarize an entire data set to describe the main features of it. Central tendency and statistical dispersion are commonly applied, where the former measures how the data is clustered around a single value and the latter measures the spread of data. On the one hand, transmissions of a hopping system are reasonably spread over its hopping channels and have a high statistical dispersion as long as the total number of captured hops is fairly large. On the other hand, a non-hopping system exhibits high central tendency, since all transmissions are expected to be in a single frequency channel. Non-hopping systems maintain cumulative moving average of incoming binary values $L_{i,j}$ as a measure of central tendency $CT_{i,j}$ as given by the membership function $\mu_{i,j}^{\text{CT}}[L_{i,j}]$:

$$CT_{i,j} = \mu_{i,j}^{\text{CT}}[L_{i,j}] = \frac{L_{i,j} + (q-1) \cdot CT_{i,j}^{\text{prev}}}{q} \tag{17}$$

where q is the total number of process frames and $CT_{i,j}^{\text{prev}}$ is the previous computed measure of central tendency. On the other side, only the first occurrence over each hopping channel is remembered for a hopping system as a measure of statistical dispersion $SD_{i,j}$. It is given by the membership function $\mu_{i,j}^{\text{SD}}[L_{i,j}]$:

$$SD_{i,j} = \mu_{i,j}^{\text{SD}}[L_{i,j}] = \begin{cases} 1 & \text{if } L_{i,j} = 1, \\ \text{unchanged} & \text{otherwise.} \end{cases} \tag{18}$$

F. Inference Layer

Finally, in the last layer a decision is made whether a present PU system is a hopping or non-hopping system. On the one hand, the membership function $\mu_i^{\text{NH}}[CT_{i,j}]$ is applied to evaluate the presence of a non-hopping PU system:

$$PU_i^{\text{NH}} = \mu_i^{\text{NH}}[CT_{i,j}] = \begin{cases} 1 & \text{if } \max\limits_{i\,=\,\text{const.}} (CT_{i,j}) \geq \gamma_i^{\text{CT}}, \\ 0 & \text{otherwise.} \end{cases} \tag{19}$$

where γ_i^{CT} is a specific threshold value for the i^{th} PU system. On the other hand, the presence of a hopping PU system is evaluated by the membership function $\mu_i^{\text{H}}[SD_{i,j}]$:

$$PU_i^{\text{H}} = \mu_i^{\text{H}}[SD_{i,j}] = \begin{cases} 1 & \text{if } \operatorname*{mean}\limits_{i\,=\,\text{const.}} (SD_{i,j}) \geq \gamma_i^{\text{SD}}, \\ 0 & \text{otherwise.} \end{cases} \tag{20}$$

where γ_i^{SD} is a specific threshold value for the i^{th} PU system.

III. Results and Analysis

The WII approach NFSC was implemented within Matlab SIMULINK as shown in 3. Thereby, the SDR Ettus USRP N210 was connected directly via Gigabit Ethernet. The implementation and setup parameters are listed in Table I.

TABLE I: Implementation and setup parameters

Parameter	Value
Center frequency f_{SDR}^{0}	2.423 GHz
Display bandwidth B^{DI}	10 MHz
Resolution bandwidth Δf	39.22 kHz
Min. incoming power density	0 dBm
Max. incoming power density	-11 dBm
Filtering constant D_i	20
Channel attenuation (coax. cable)	2 dB
Transmission power	0 dBm

A. Measurement Metrics

First of all, although the NFSC's last two layers are proposed in [7] for distinguishing between a hopping and a non-hopping PU system, the evaluation of the NFSC is carried out directly through the also recorded similarity measure. The similarity measure for all corresponding PU frequency channels were recorded for ten seconds.

As a first step of the statistical analysis, a normalized frequency distribution, also known as empirical probability, is computed from the SM. All histograms were created with 100 bins for the similarity interval from zero to one. As the second step, all histograms from all recorded frequency channels are compared with each other. As the last step, mean and standard deviation are computed for each frequency channel out of the corresponding histograms.

The classification performance of the NFSC is evaluated through the two statistical measures: sensitivity and specificity. Sensitivity and specificity are statistical measures of the performance of a binary classification test. They measure the proportion of actual positive and negative decisions which are correctly identified as such, respectively. With the amount of correctly identified classes TP, incorrectly identified classes FP, correctly rejected classes TN, and of incorrectly rejected classes FN, sensitivity *TPR* and specificity *TNR* are defined as $\mathit{TPR} = \mathit{TP}/(\mathit{TP} + \mathit{FN})$ and $\mathit{TNR} = \mathit{TN}/(\mathit{TN} + \mathit{FP})$ which is also known as true and negative positive rate, respectively.

B. Industrial Scenarios

Since this paper focuses on system classification within the 2.4-GHz-ISM radio band in an industrial environment,

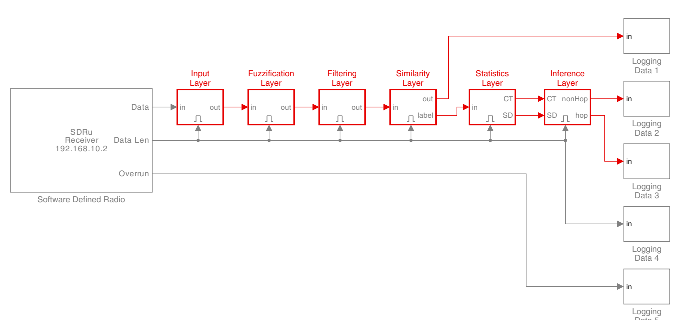

Fig. 3: Matlab SIMULINK implementation block diagram of NFSC layers

TABLE II: Selected industrial wireless scenarios

Industrial	Channels		Temp. medium occupancy	
scenario	WLAN	Bluetooth	WLAN	Bluetooth
1	1	-	84.47%	-
2	1	-	30.68%	-
3	-	1, 2, ..., 79	-	39.36%
4	-	1, 2, ..., 79	-	20.80%
5	1	23, 24, ..., 79	84.47%	39.36%
6	1	23, 24, ..., 79	30.68%	20.80%

two standard wireless technologies are chosen as example PU system. It is assumed that an industrial automation is equipped with a WLAN (IEEE 802.11g) as a base infrastructure. On the other hand, Bluetooth is used as a wireless PAN at electrical machines, such as for transmitting sensor data of an industrial robot. Thereby, the scenarios are utilized with high and low temporal medium occupancy load. An overview of the utilized industrial scenarios in this evaluation is presented in Table II.

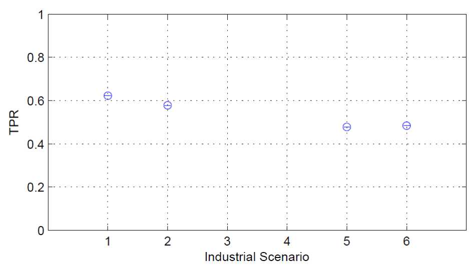

Fig. 4: Sensitivity of all industrial scenarios classified as WLAN

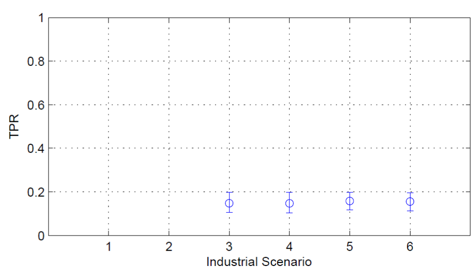

Fig. 5: Sensitivity of all industrial scenarios classified as Bluetooth

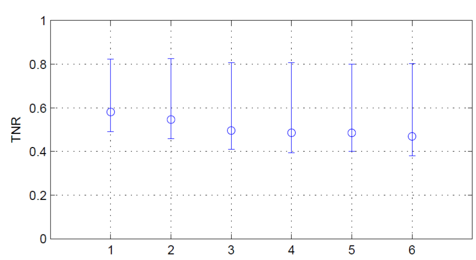

Fig. 6: Specificity of all industrial scenarios classified as WLAN

C. Experimental Results

The outcome of the evaluation as depicted in Figure 4, 5, 6 and 7 was a low sensitivity of the NFSC throughout all

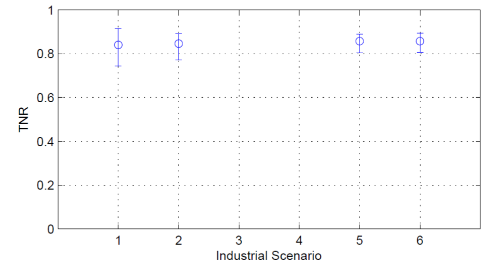

Fig. 7: Specificity of all industrial scenarios classified as Bluetooth

industrial scenarios, while specificity was measured in general high. Averagely, IEEE 802.11g was detected with a moderate rate of 55% and Bluetooth only with 15%. On the contrary, a typical specificity of 50% were measured. For Bluetooth even up to 90%.

IV. Conclusion

An efficient implementation of a WII approach called neuro-fuzzy signal classifier (NFSC) for industrial wireless environments was implemented and evaluated. The implementation in Matlab / SIMULINK is based upon a wideband software defined radio system Ettus USRP N210. Furthermore, a classification performance evaluation was performed in six selected heterogeneous and harsh industrial scenarios within the license-free 2.4-GHz-ISM radio band with variously combined standard wireless technologies IEEE 802.11g-based WLAN and Bluetooth. The evaluation of the NFSC was performed by a binary classification test with the statistical measurement metrics sensitivity and specificity.

The results show that absent PU systems are better detected by the NFSC as present ones. NFSCs scope of application is, therefore, rather detecting free gaps in its radio resources than identifying PU systems by their utilized standard wireless technologies.

V. Acknowledgments

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