Chapter

Industrial IoT Using Wavelet Transform

Mohamed Tabaa, Safa Saadaoui, Mouhamad Chehaitly, Aamre Khalil, Fabrice Monteiro and Abbas Dandache

Abstract

For many years now, communication in the industrial sector has been characterized by a new trend of integrating the wireless concept through cyber-physical systems (CPS). This emergence, known as the Smart Factory, is based on the convergence of industrial trades and digital applications to create an intelligent manufacturing system. This will ensure high adaptability of production and more efficient resource input. It should be noted that data is the key element in the development of the Internet of Things ecosystem. Thanks to the IoT, the user can act in real time and in a digital way on his industrial environment, to optimize several processes such as production improvement, machine control, or optimization of supply chains in real time. The choice of the connectivity strategy is made according to several criteria and is based on the choice of the sensor. This mainly depends on location (indoor, outdoor, …), mobility, energy consumption, remote control, amount of data, sending frequency and security. In this chapter, we present an Industrial IoT architecture with two operating modes: MtO (Many-to-One) and OtM (One-to-Many). An optimal choice of the wavelet in terms of bit error rate is made to perform simulations in an industrial channel. A model of this channel is developed in order to simulate the performance of the communication architecture in an environment very close to industry. The optimization of the communication systems is ensured by error correcting codes.

Keywords: industrial IoT, wireless communication, DWPT, IDWPT, many-to-one, one-to-many, industrial channel, ECC

1. Introduction

In recent years, technological developments in wireless communication systems have improved user needs in terms of accessibility, data quantity, intelligent decision making and energy consumption. These technologies are still evolving, thanks to the integration of new techniques to improve the connectivity of billions of objects. These connected objects, whether sensors or actuators, are by nature autonomous physical devices with a limited energy source [1, 2]. They are able to communicate with each other, creating a technological revolution. This revolution is bringing more ambitious innovations in a variety of application areas: medicine, industry, energy, security and others.

For industrial applications, research is focused on creating connected, robotic and intelligent factories to improve current production systems. This interconnection of factories is achieved through the connected systems, in which employees, machines and products collaborate with each other to form the new revolution. At the heart of this revolution, the Industrial Internet of Things (IIoT) plays a key role in the development of connectivity for this revolution (**Figure 1**) [3, 4]. In such an industrial environment, propagation differs from other conventional indoor means of communication through its large dimensions and the nature of the objects and obstacles inside. Thus, the industrial environment can be modeled as a fading channel affected by impulsive and Gaussian noise [5, 6].

Given the major advantage of connectivity in the industrial environment, it is necessary to propose wireless, robust and efficient communication architectures inside the factory. The design of these systems differs for each application, taking into account the constraints of the propagation environment. Unlike other traditional indoor environments such as residential buildings or offices, this environment is characterized by its large dimensions and also by the nature of its elements and obstacles. The complexity of the industrial context as well as the noise present in the propagation environment make it necessary to offer a robust wireless communication system to cope with the various disturbances during transmission [5, 7].

In this chapter we focus on applications of industrial communication in a high noise industrial environment. In this work, a multi-user wireless communication system is proposed, characterized by two distinct modes of operation. The first mode provides "Many-To-One" (MtO) communication between several transmitters and a single receiver. The second mode allows one transmitter sensor to send to several receivers in One-To-Many (OtM) mode. These modes of communication illustrate the links between the first three levels of the CIM (Computer-Integrated Manufacturing) pyramid, of which this pyramid illustrates the industrial model on 5 levels. The proposed communication architecture is based on the transformation of wavelet packets The use of the wavelet transform in this context consists, on the one hand, in generating several forms of impulses via their synthesis and being able to simply assign them to each user, and, on the other hand, in the reconstitution of these impulses by the receiver, thus providing an analysis method that is simple to implement and effective. These techniques of analysis and synthesis constitute the major advantage of the wavelet transform for pulse modulations.

An optimal choice of the wavelet in terms of binary error rate is made to perform simulations in an industrial channel. A model of this channel is developed in order to simulate the performance of the communication architecture in an

Figure 1.
IIoT communication in the context of smart factory.

environment very close to industry. Naturally, the optimization of the communication systems is ensured by error correcting codes, this is how we proceeded. We have optimized the performance of our system architecture through conventional channel coding.

This chapter will be presented as follows: in the second part, the state of the art concerning Industry 4.0 and IIoT is developed. The study concerning the discrete wavelet packet transform is discussed in the third part. The part describes the functioning of the proposed architecture in two modes MtO and OtM. the industrial channel model is discussed in the fifth part. The sixth part presents the simulation results and towards the end a conclusion.

2. State of art

2.1 Industry 4.0

Industry 4.0 is characterized by a new way of organizing plants to put an end to complex hierarchical structures. Therefore, ICT techniques must be merged with industrial technologies. In Industry 4.0, embedded systems, IoT and CPS technologies link virtual space to the physical world to give birth to a new connected generation of so-called "intelligent" factories. These factories are capable of more efficient allocation of production resources, with the main objectives of customizing products, minimizing time to market and improving business performance. This opens the way to a new mode of industrial transformation. The concept of Industry 4.0 was first introduced at the Hanover Industrial Technology Fair in 2011, the world's largest technology and industrial trade fair. In 2013, Germany officially adopts the implementation of the concept by the German government's identification of Industry 4.0 in its future projects within its action plan "High-Tech Strategy 2020" (**Figure 2**).

It has rapidly evolved as a German national strategy based on 4 aspects: Building the CPS network, addressing two main themes based on the plant and intelligent production, thus achieving 3 types of integration: Horizontal, vertical and point-to-point. The result is that German industry has welcomed the initiative with open arms. Small, medium and large companies from all sectors participated in the creation of this new era. However, the boost from the government has helped to internationalize the concept of Industry 4.0. In 2014, the State Council of China unveiled its national plan, Made-in-China 2025, inspired by Industry 4.0 and

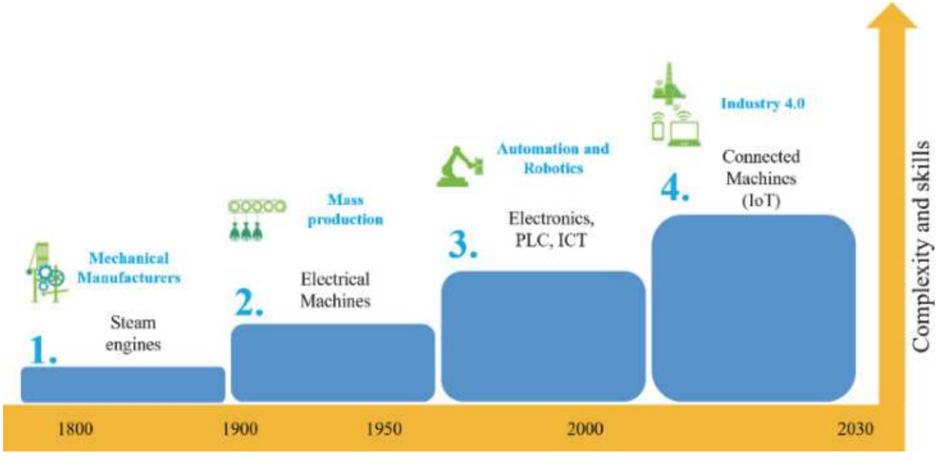

Figure 2.
Evolution of the industry.

designed to improve China's industry globally, integrating digital and industrial technologies. At the same time, several countries have adopted this concept, we cite as an example "the new industrial France" by France, "Industrial internet and advanced manufacturing partnership in USA" by the United States [8, 9].

2.2 IIoT vs. IoT

In the last few decades, technological developments in wireless communication systems have improved user needs in terms of accessibility, data quantity, intelligent decision making and energy consumption. These technologies are still evolving, thanks to the integration of new techniques to improve the connectivity of billions of objects. These connected objects, whether sensors or actuators, are by nature autonomous physical devices with a limited energy source. They are able to communicate with each other, creating a technological revolution. This revolution is bringing more ambitious innovations in a diverse range of applications: medicine, industry, energy, security and others [10, 11].

For industrial applications, research is focused on creating connected, robotic and smart factories to improve current production systems. This interconnection of factories is achieved through the connected systems, in which employees, machines and products collaborate with each other to form the new revolution. At the heart of this revolution, the IIoT plays a key role in the development of connectivity for this revolution. Based on the same concept of IoT, IIoT is based on the use of connected sensors or actuators to improve industrial processes and manufacturing. It integrates intelligence in data processing and analysis to ensure better M2M (Machine-to-Machine) communication. This has been in existence since the integration of electronics in the industrial sector during the third "industry 3.0" revolution. It is now necessary to work on robust communication architectures allowing objects and the technological choice of communication technologies and protocols, in a highly noisy industrial environment, to communicate easily in order to build reliable information for better decision making [12, 13].

General Electric presents the Industrial Internet as a term meaning the integration of complex physical machines with networked sensors and software. The Industrial Internet brings together areas such as IoT, Big Data, machine learning and M2M (Machine to Machine) communication to collect and analyze machine data and use it to adjust operations.

According to the Industrial Internet Consortium IIC, the Industrial Internet connects intelligent devices and machines with people at work, enabling better decisions through advanced analysis that leads to transformational business outcomes. The Industrial Internet covers the non-consumer side of the IoT and applies "internet thinking" to industrial environments.

The Industrial Internet consists of three key elements that together represent the essence of the idea:

- Smart machines: this means connecting machines, fleets, facilities and networks around the world with advanced controls, sensors and software applications.

- Advanced analysis: means combining the power of physics-based analysis, domain expertise, automation and predictive algorithms to understand how machines and systems work.

- People at work: essentially means connecting people at all times to support smarter operations, design and maintenance, as well as high quality of service and safety.

The connection and combination of these three key elements allows companies and economies to benefit from many new opportunities and efficiency gains in several areas. The industrial internet will accelerate productivity growth in the same way that the industrial revolution and the internet revolution have done in the past.

3. Wavelet packet discrete transform

As a matter of principle, the multiresolution analysis in $L^2(R)$ space of the continuous functions of a real variable and an integrable square can be extended to subspaces of it. That is, the same scheme can be applied to the W_j subspaces generated by the previous analysis. Figure shows the hierarchy of the wavelet packet decomposition: it illustrates the principle of wavelet packet decomposition through the analysis of all subspaces [14]. **Figures 3** and **4** illustrate the principle of this decomposition by the discrete wavelet transform.

The analysis used in the wavelet packet transform leads to a decomposition into frequency sub-bands of the input signal. This analysis can be carried out either by the same scale and wavelet functions, which is usually the case, or by different functions. This makes it possible to change the basic functions at each scale. It can be said that perfect reconstruction is ensured by reusing during synthesis, and for a precise resolution of the base functions combined with those used during the analysis at this same resolution. The procedure of analyzing subspaces of signal detail in addition to the approximation subspaces is generally referred to as "wavelet packet analysis."

Because this transform presents a good symmetry of structure which results in identical sampling frequencies on all the inputs of the synthesis filter bank, and on all the outputs of the analysis filter bank, our choice was directed towards an implementation of the discrete wavelet packet transform. This approach will facilitate the generation of the pulses and be able to identify their content (nature of the transmitter, or value of the transported data) [15].

3.1 Packet wavelet transform

The main objective of the wavelet packet decomposition is to extend the construction of a new base from all generated subspaces. By definition, the

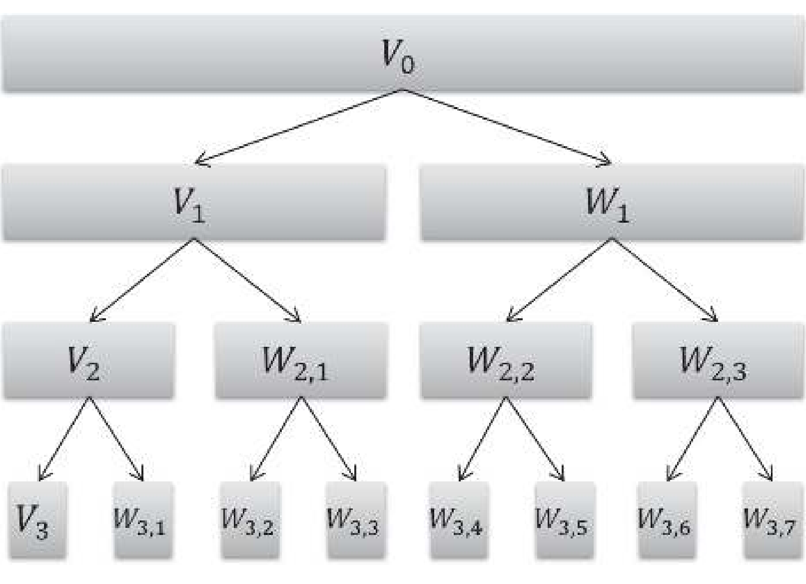

Figure 3.
Discrete wavelet transform decomposition principle.

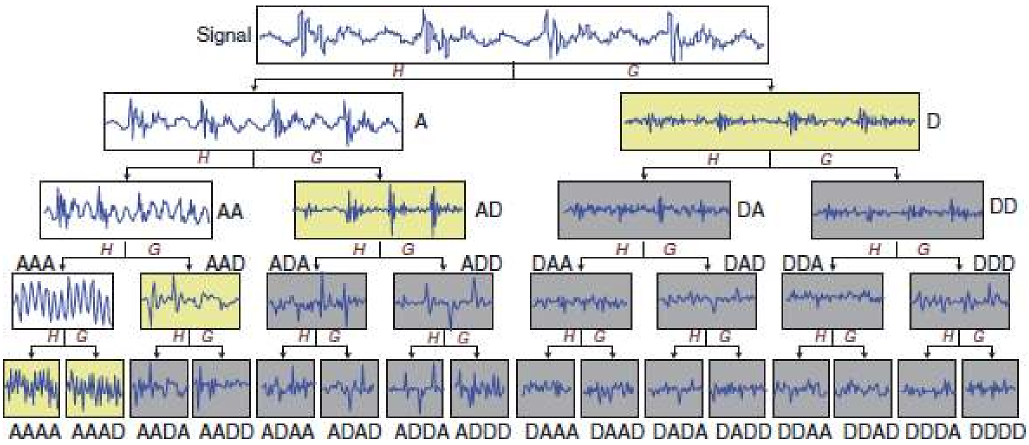

Figure 4.
Scale 4 decomposition procedure by discrete wavelet packet transform. H represents the low-pass filter and G the high-pass filter.

multiresolution analysis of an approximation space V_j is decomposed into two lower resolution spaces V_{j+1} and W_{j+1} [16]. Therefore, this division is obtained by transforming the base $\left\{\phi_j\left(2^{j+1}t-k\right)\right\}_{k\in Z}$ de V_j in two orthogonal bases: $\left\{\phi_{j+1}\left(2^{j+1}t-k\right)\right\}_{k\in Z}$ de V_{j+1} et $\left\{\psi_{j+1}\left(2^{j+1}t-k\right)\right\}_{k\in Z}$ for W_{j+1}.

Note P this tree in which each node corresponds to a subspace P_j^n which admits an orthogonal base $\left\{P_j^n(t-k)\right\}_{k\in Z}$. At a resolution level j we will have:

$$P_j^n = P_{j+1}^{2n} \oplus P_{j+1}^{2n+1.} \tag{1}$$

The functions obtained are wavelet packets that are recursively determined by:

$$P_{j+1}^{2n}(t) = \sqrt{2}\sum_k h(k)p_{j+1}^{2n}(2t-k) \tag{2}$$

$$P_{j+1}^{2n+1}(t) = \sqrt{2}\sum_k g(k)p_{j+1}^{2n}(2t-k) \tag{3}$$

It should be noted that:

p_0^0 represents the scaling function and p_0^1 the associated wavelet via multiresolution analysis and noted respectively ϕ and ψ.

The filters h_n and g_n are respectively the low-pass and high-pass filters represented by quadrature mirror filters, and linked by the following equation:

$$\mathrm{G(n)} = (-1)^{\mathrm{n}}\mathrm{h}(1-\mathrm{n}) \tag{4}$$

The impulse response of the filters satisfies the following conditions:

$$\sum_n h(n-2k)h(n-2l) = \delta_{kl} \ \&\sum_n h(n) = \sqrt{2} \tag{5}$$

$$\sum_n g(n-2k)g(n-2l) = \delta_{kl} \ \&\sum_n g(n) = 0 \tag{6}$$

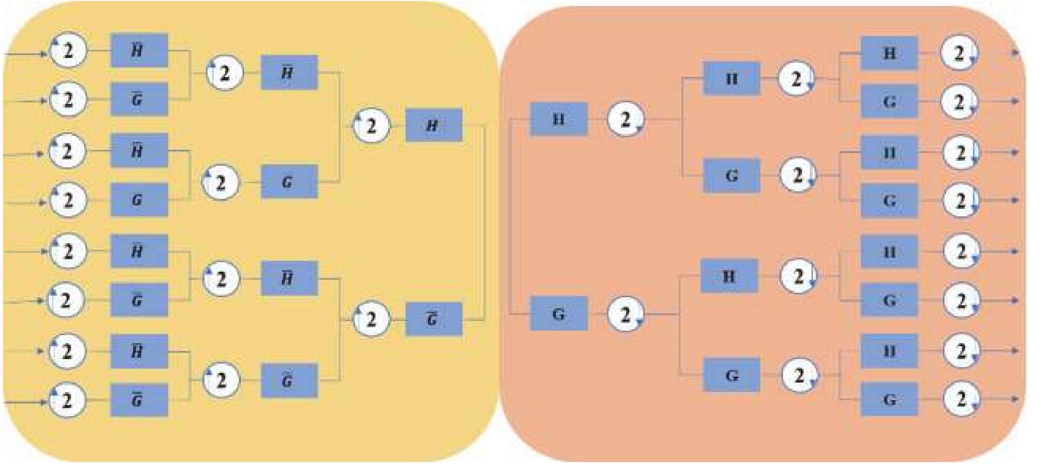

Figure 5.
IDWPT-based transmitter and DWPT-based receiver.

3.2 Decomposition and reconstruction

Recall that each function f(t) in the $L^2(R)$ space can be decomposed on the basis of functions $\{p^n_{j,k}(t)$, where (j,k)ϵZ*Z} as follows:

$$F(t) = \sum_{n,k} a^n_{j,k} p^n_{j,k}(t) \tag{7}$$

with j the depth of decomposition, k the time index, and n the frequency index equivalent to the wavelet number.

The coefficients $a^n_{j,k}$ at a given scale j are expressed as a scalar product of the signal to be analyzed and the analyzing function:

$$a^n_{j,k} = \left\langle f, p^n_{j,k} \right\rangle = \int_{-\propto}^{+\propto} f(t) p^n_{j,k}(t) dt \tag{8}$$

The wavelet packet decomposition is shown in **Figure 5**. In this example, the wavelet packet analysis of the function f is performed with a depth of 4.

The set of coefficients $a^n_{j,k}$ constitutes the discrete wavelet packet transform (DWPT) of f(t) and its inverse transform (IDWPT) is given by:

$$a^n_{j,k} = \sum_{i \in Z} h_{k-2i} a^{2n}_{j,k} + \sum_{i \in Z} g_{k-2i} a^{2n+1}_{j,k} \tag{9}$$

The wavelet packet transform simply consists of filtering the signal using a low-pass filter h_n and a high-pass filter g_n. As for synthesis, it is a regrouping of the signals into a single signal that represents the signal already analyzed. These two approaches give rise to filter banks that check the following conditions:

$$\bar{h}_n = h_{-n} \text{ et } \bar{g}_n = g_{-n} \tag{10}$$

4. Proposed communication architecture

In this chapter, two multi-user operating modes have been studied and tested: the "Many-to-One" mode (MtO) and the "One-to-Many" mode (OtM). The choice of these modes depends essentially on the existence in the current communication architectures (master-slave, bidirectional), in order to facilitate adaptation for a better integration [17–19].

4.1 Many-to-One mode

The MtO mode corresponds to multi-sensor communication from several sensors to a single receiver (**Figure 6**). Each transmitting sensor is in the form of an IDWPT block ensuring the activation of a single input for this transmitter, which allows the transmitting sensor to be identified already. Therefore, each input of the IDWPT block on transmission corresponds to a single output of the DWPT block on reception.

Based on the CIM pyramid (**Figure 7**), this mode of communication corresponds to a communication from level 0 and 1 to level 2. In this mode, data from one or more low flow sensors are transmitted at the same time to the same receiver, and

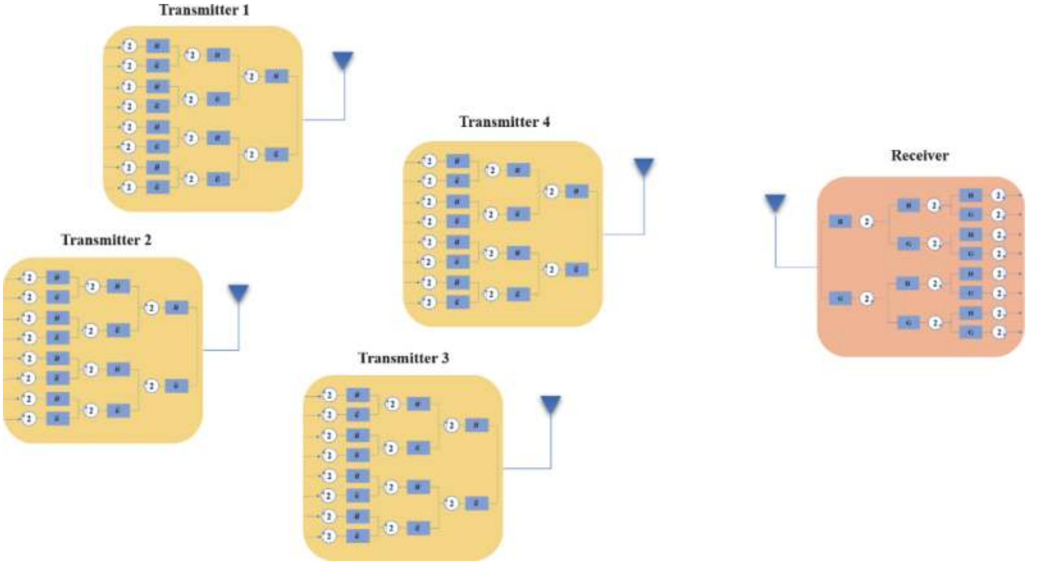

Figure 6.
Many-to-One mode.

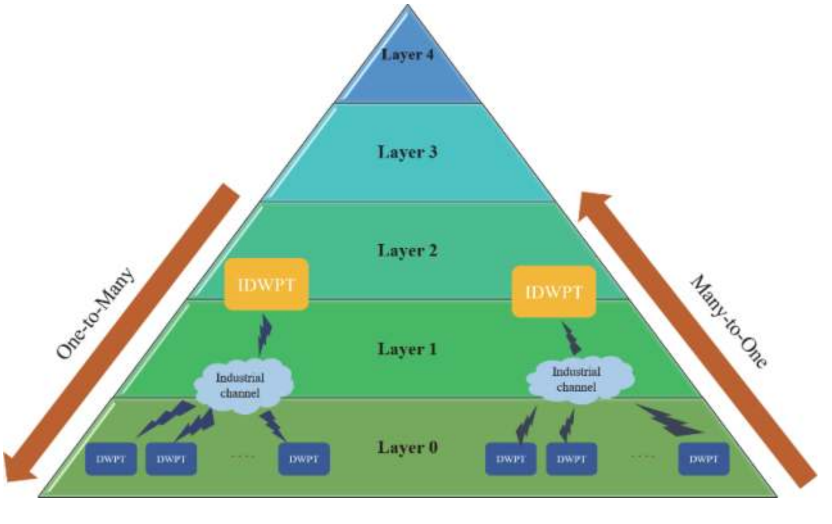

Figure 7.
Operation of MTO and MtO modes in the CIM pyramid.

the activation of one of the inputs generates the activation of a user. **Figure 8** illustrates an 8-input architecture corresponding to 8 potential sensors (scale 3). Therefore, each transmitter uses a single input that is different from the other inputs. The pulse shape of each activated input is different from the waveforms of the other inputs, the other non-activated inputs will be set to zero.

The DWPT-based receiver receives the data stream from all transmitters at the same time. However, each sensor is identified by a unique filter output at the receiver that represents the same input at the receiver. This mode has a higher bandwidth occupancy than single user mode because each user (input enabled) will occupy a separate sub-band. This will result in frequency selectivity of the channel due to interference between users, for which it will be necessary to protect the

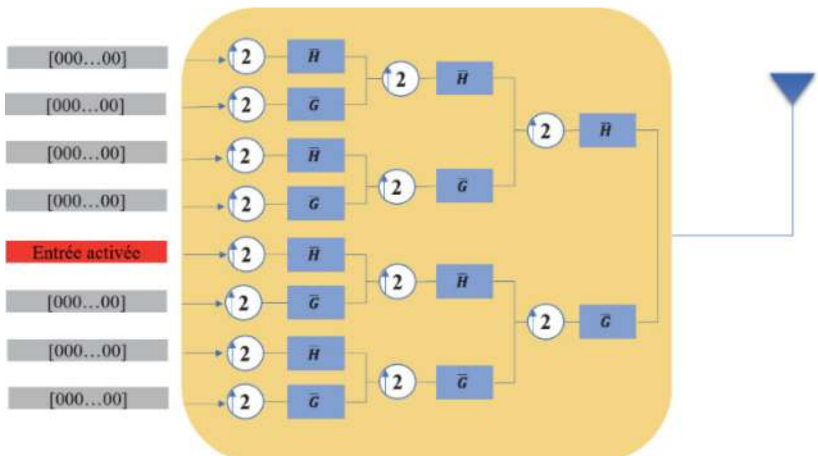

Figure 8.
Transmitter operation in MtO mode.

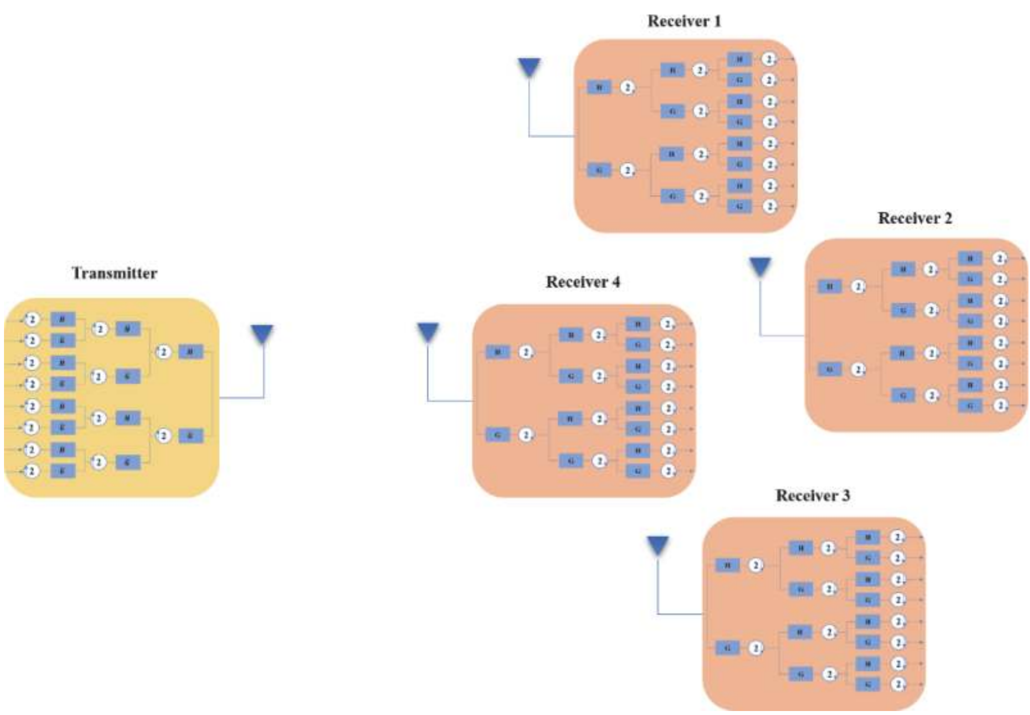

Figure 9.
One-to-Many mode.

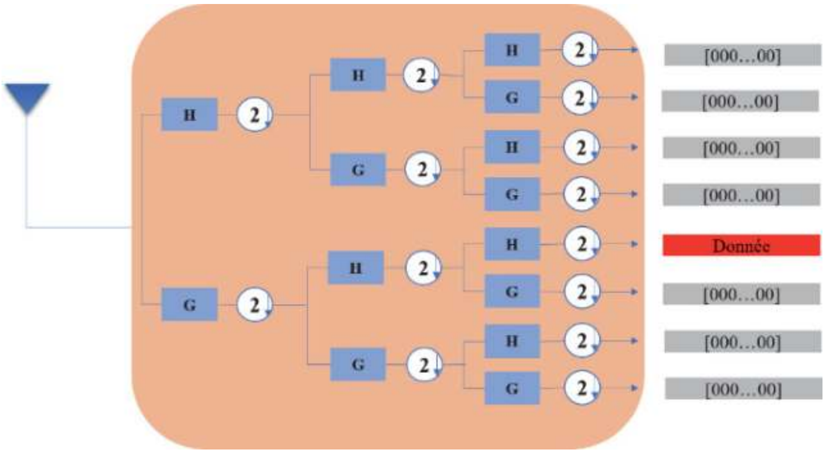

Figure 10.
Receiver in one-to-many mode.

transmitted data as much as possible. Nevertheless, this will allow synchronous communication of several sensors to the same receiver.

4.2 One-to-Many mode

For the OtM mode, an IDWPT transmitter is characterized by n inputs, capable of sending information to m DWPT receivers with n outputs each.

Note that the information sent via input (i) is retrieved at output (i). This is the inverse mode of the MtO mode where the equipment's of levels 1 and 2 of the CIM pyramid send the same information to the level sensors. This mode is equivalent to the master-slave architecture in a conventional industrial communication system. Although the data rate of the transmitted data is generally low, the reception of information from several sensors creates spatial diversity that allows the data to be retrieved by at least one receiver. **Figure 9** illustrates the transmission of data from a single sensor to 4 receivers. The data sent will be detected in the 5th output of the 4 receivers, as shown in **Figure 10**.

5. Industrial channel

Signals in an industrial environment are subject to several disturbances due to propagation phenomena. These disturbances significantly degrade system performance. This environment is affected by very complex noise and interference caused by machine temperatures, vibrations, metal structures and heavy machinery [SHA09]. In addition, the signal is subject to attenuation and shadowing effects caused by abstractions in the propagation channel. The mobility of equipment and people in the wireless medium can also cause time-varying effects. These effects can significantly destroy the information exchanged and thus degrade any communication system performance in the industry [CHE16]. Therefore, it is necessary to estimate the propagation channel in order to design and evaluate the entire wireless transmission system for industrial applications.

5.1 Fading

For wireless propagation in an industrial context, the received information is subject to attenuation and fading effects, of which the expression of the received signal is:

$$y(t) = h(t) * s(t) + n(t) \tag{11}$$

Where, h(t) is the channel impulse response, s(t) is the transmitted signal and n(t) is the additive noise.

In a factory, sensors/actuators are usually arranged according to the production system configuration. Measurements of narrowband and broadband indoor channels have been performed through research in several industrial environments [20], and have shown that the time impulse response h(t) at a fixed location in an industrial context follows a reduced exponential distribution [21, 22]. This distribution depends mainly on the delay and power of each channel, which is shown in Saleh Valenzuela's model [23]. The delay spread of the channels can be determined from the impulse response as a function of the transmission frequency and the LOS (Line-Of-Sight) or NLOS (Non-Line-Of- Sight) configurations. Thus, the objective of the research work is to validate the IDWPT/DWPT-based architecture under a simulated industrial channel, and we then generated a channel impulse response based on the measurements from the work [24, 25] for both LOS and NLOS configurations at 2.4 GHz. The simulated channel impulse response includes 10 significant paths (**Figure 11**).

In order to represent a channel fading phenomenon, all paths follow the same statistical distribution [26]. The time envelope of the received signal follows the Rician statistical distribution in the LOS scenario and the Rayleigh distribution in the NLOS case.

$$P(x) = \frac{x}{\sigma^2} exp\left(-\frac{x^2 + K^2}{2\sigma^2}\right) I_0\left(\frac{Kx}{\sigma^2}\right) \tag{12}$$

With $I_0(x)$ is the Bessel function changed to zero order. K is the shape parameter called Rician factor. For K = 0, P(x) converges to the Rayleigh distribution.

5.2 Noise

In the case of wireless communication systems, the noise added to the received signal is White Gaussian Noise (WGN additive). In an industrial environment, the signals will be affected by noise, which is represented as impulsive noise from motors, regulators, electrical equipment and others. However, the industrial noise $n(t)$ in equation will be modeled as a superposition of AWGN w(t) and impulsive

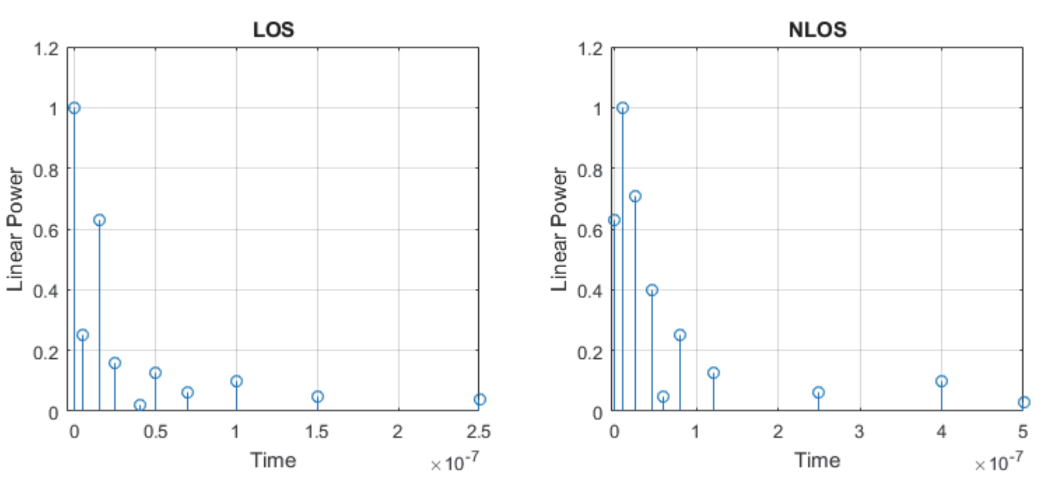

Figure 11.
Simulated channel impulse response.

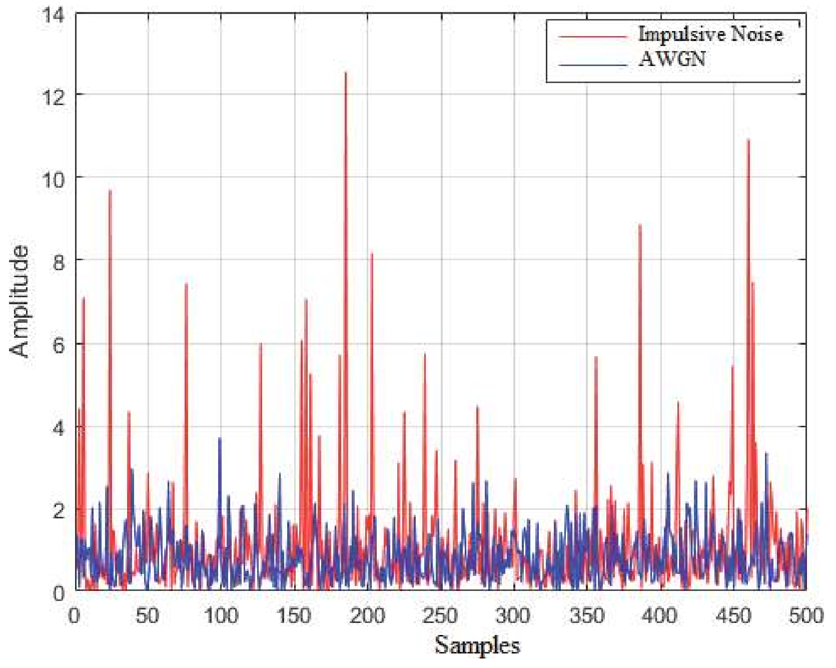

Figure 12.
Industrial noise with a scale factor R = 50.

noise $i(t)$ having a very high variance. Then, $i(t)$ is modeled as a two-state first-order Markov process thus describing the typical impulsive noise [27] (**Figure 12**).

$$n(t) = w(t) + i(t) \tag{13}$$

where $w(t)$ and $i(t)$ are zero-mean Gaussian processes whose probability density functions are respectively:

$$P[w(t)] = \frac{1}{\sqrt{2\pi\sigma^2}} exp\left[-\frac{w(t)^2}{2\sigma^2}\right] \tag{14}$$

$$P[i(t)] = \frac{1}{\sqrt{2\pi R\sigma^2}} exp\left[-\frac{i(t)^2}{2R\sigma^2}\right] \tag{15}$$

With $R \geq 1$ is a scale constant of the amplitude of the impulse noise. The higher the amplitude, the greater the noise. For our simulations, we use R = 50 which corresponds to significant impulse noise.

6. Simulations, results and performances

In this section, we will present the simulation results of the IDWPT/DWPT architecture under a noisy industrial channel. All the simulations presented in this chapter are performed under MATLAB.

6.1 Simulations and results

The proposed system is based on a multi-user IDWPT/DWPT architecture for 2^n sensors/actuators in an industrial environment. The transmitters are based on the IDWPT implementation in the form of synthesis filter banks, and the receivers are based on DWPTs implemented as analysis filter banks. The industrial channel is described as a Rician fading channel for the LOS configuration and a Rayleigh fading channel for the NLOS configuration at the 2.4GHz frequency affected by impulsive noise. In our simulations, we choose the "Symlet" wavelet that has demonstrated the lowest bit error rate for the IDWPT/DWPT architecture under an AWGN channel (**Figure 13**).

In the case of the MTO mode in multi-sensor configuration, the frames for each user are 16 bits long and randomly generated. This data configuration is due to the fact that sensors in industrial environments transmit short data packets. These data frames are pulse modulated and each transmitter is identified by a unique signal. **Figure 14** shows the signals from 4 different sensors (1, 5, 12 and 16) in an architecture with 16 transmitter sensors. The 16 generated signals are all different from each other because the binary data at the input of each filter are different.

Based on the effect of channel fading due to delay propagation in addition to AWGN noise for the LOS and NLOS configurations, it is clear that the multipath effect disturbs the signals of the different users and thus causes interference between them. The proposed architecture allows signal detection at reception for all users as shown in **Figure 15** for a SNR (Signal to Noise Ratio) greater than 20 dB [27–33].

With fading effects, and the addition of industrial noise composed of Gaussian noise and impulse noise, the bit error rate is shown in **Figure 15**. The communication architecture converges more slowly and performance decreases, but it allows the full information of an SNR up to 35 dB. In the case of industrial noise, the data may be completely lost if the effects of the channel are not properly taken into account.

In the case of the OtM mode, a single transmitter based on DWPT with n inputs sends data to m receivers based on DWPT with n outputs each. The principle of this mode is to activate only one input (i) of the transmitter and force the others to zero. When receiving, the data will be detected at output (i) of each receiver. The data are modulated through pulse modulation using a "Symlet" pulse. **Figure 16** shows

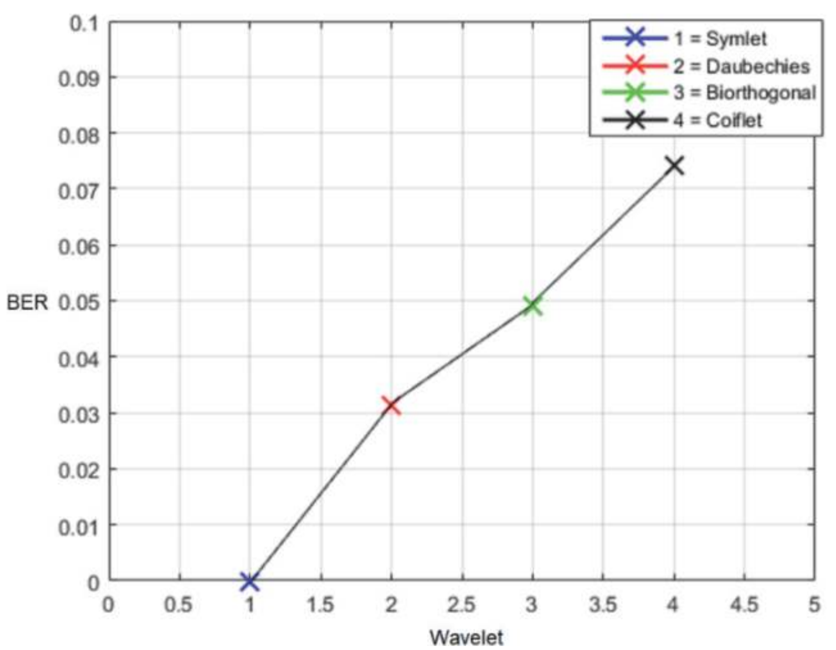

Figure 13.
Performance of four wavelets.

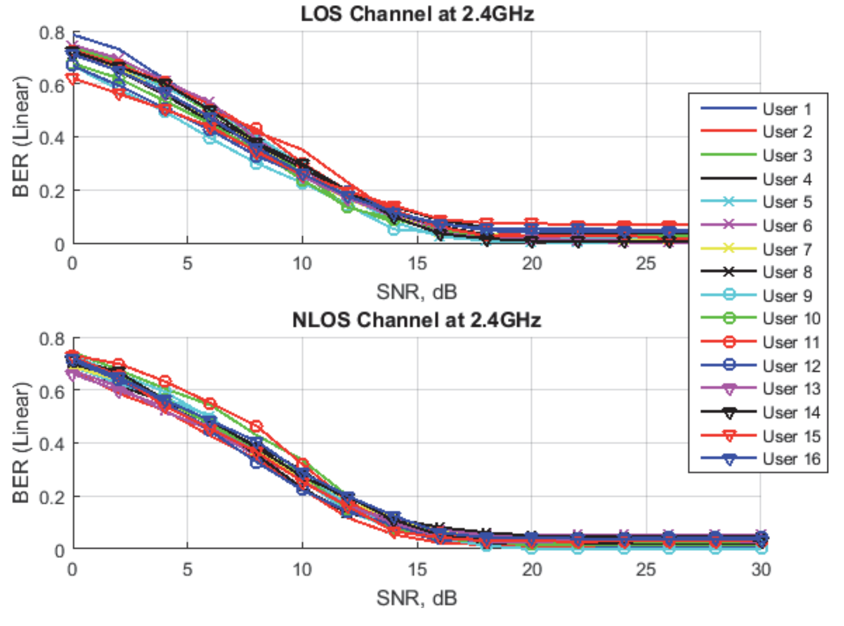

Figure 14.
BER/SNR on a fading channel with AWGN noise for MtO mode.

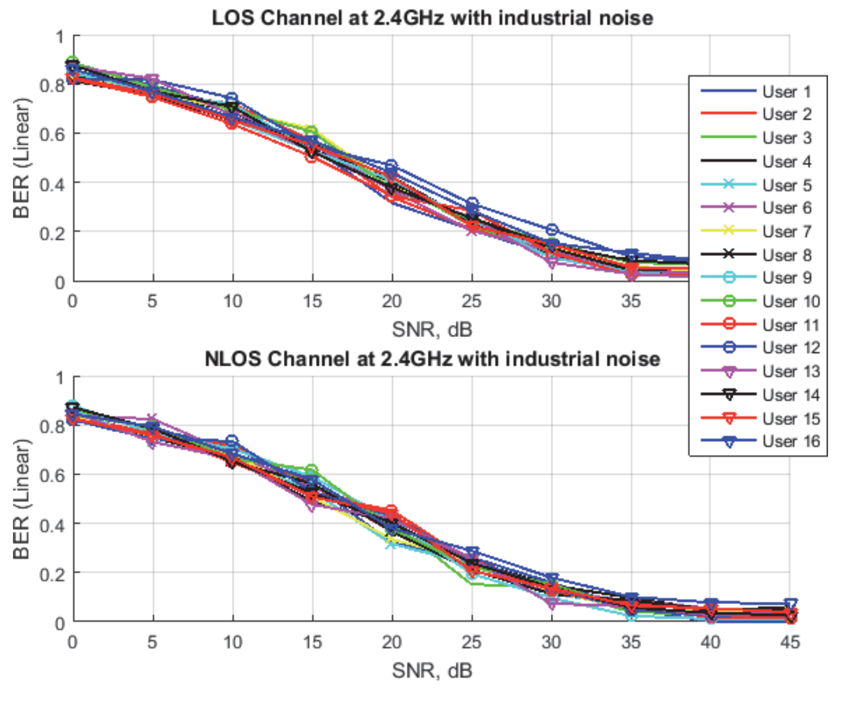

Figure 15.
BER/SNR on a fading channel with industrial noise for MTO mode.

the signals received at the 4 receivers. The data is recovered at the 7th output corresponding to the activated input.

Based on the fading channel and AWGN noise for LOS and NLOS configurations, the architecture detects the signal on reception. According to the simulation results shown in **Figure 16** the transmitted signal is detected at the receiving sensor array for the LOS and NLOS channels at 2.4 GHz. Detection is virtually error-free above 20 dB. Some differences between the LOS and NLOS configurations are

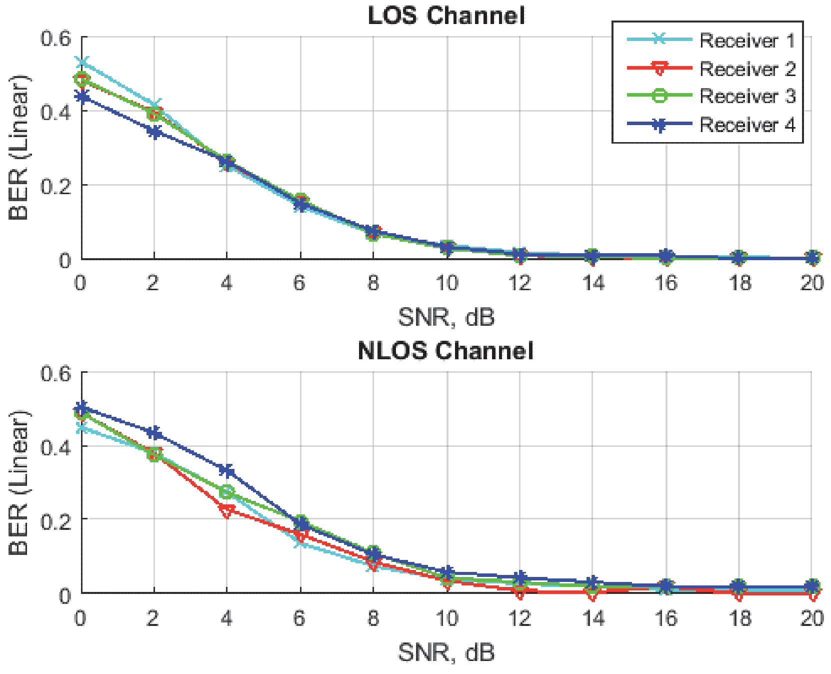

Figure 16.
BER/SNR on a 2.4 GHz fading channel with AWGN noise for OTM mode.

detected from an SNR of 14 dB. This is mainly due to the effects of channel fading and channel dispersion which must be corrected using channel coding during transmission. Taking into account the effect of industrial noise, the communication architecture allows the full detection of 30 dB SNR information as shown in **Figure 17**. The difference in error rate is very large and depends on the propagation channel.

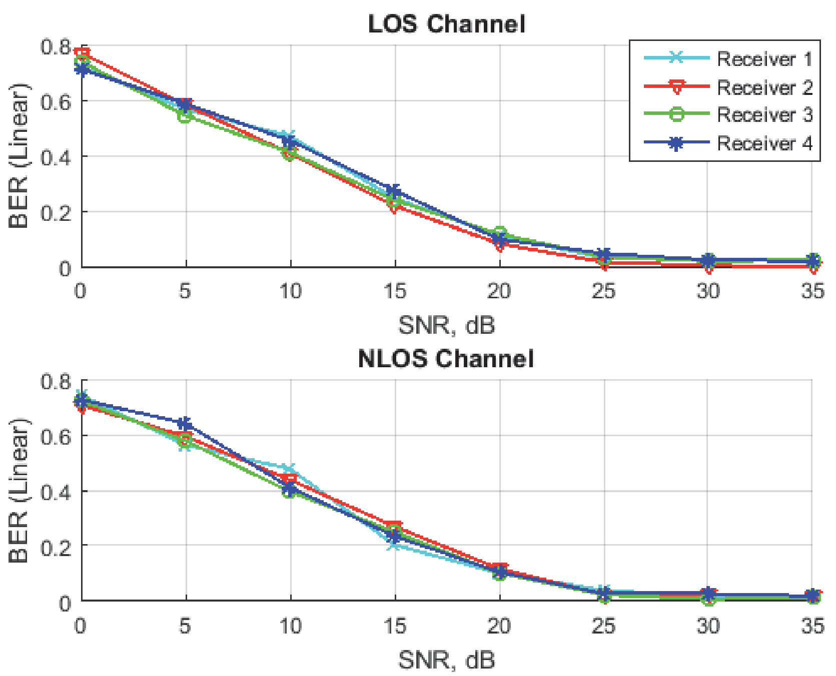

Figure 17.
BER/SNR on a fading channel with industrial noise for OTM mode.

6.2 Performances: ECC

To improve the reliability of the architecture compared to the industrial fading channel, we propose to add an error-correcting channel code on the transmitter side (**Figure 18**). We use two coding techniques: a convolutional code and RS (Reed Solomon) codes. For the convolutional code, we choose an encoder using a trellis diagram with a generating polynomial matrix of having a constraint length of 7 and a code rate = 1/2. On the receiver side, we use a Viterbi decoder [28–30].

As for the Reed Solomon encoder, we use an RS(31,17) with 31 code word symbols and 17 message symbols based on the length of the transmitted data.

As shown in **Figure 19** for an architecture with 8, 16 and 32 users on an industrial channel with AWG noise fading, the error correction code improves the robustness of the architecture against channel fading as a function of the number of sensors used. For a better graphical representation, we have shown the results for only 4 users in each case; for 8 users (user 1, 3, 5 and 7), for 16 users (user 1, 6, 12, 16) and for 32 users (user 1, 12, 22 and 30).

For a fading channel with AWG noise, the SNR is reduced by 2 dB using both convolutional and RS code for an 8-user (or sensor) architecture, and by 4 dB for RS

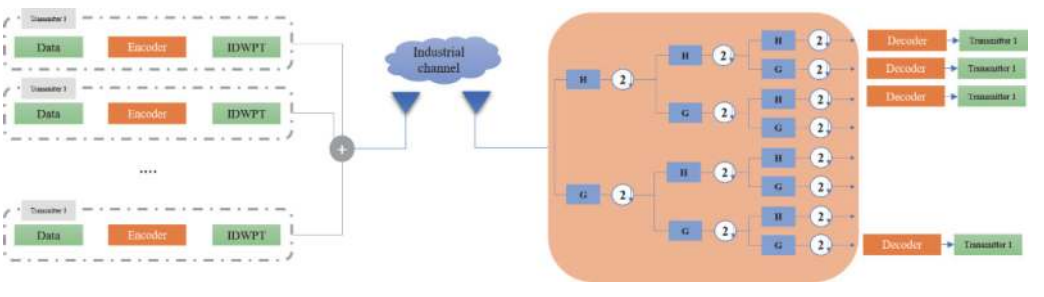

Figure 18.
Architecture for 8 sensors with channel coding.

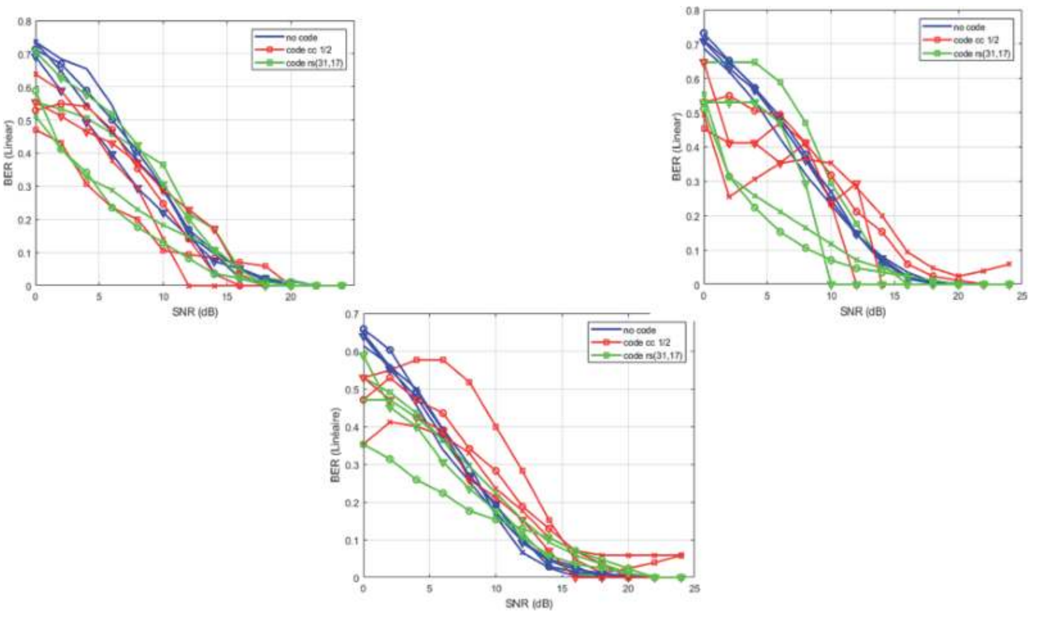

Figure 19.
BER/SNR on a fading channel with AWGN noise for MTO mode.

code in the case of a 32-user use. For a fading channel with industrial noise, the signal-to-noise ratio is reduced by 8 dB for an architecture with 16 users using a convolutional code and by 5 dB for 32 users using an RS code, as shown in **Figure 20**. For a better illustration, **Table 1** shows the different SNR values for a fixed linear bit error rate of 0.1 with or without error-correcting coding [31, 32].

We conclude that for communication over an industrial fading channel, RS coding is optimal for a 32-user architecture. However, convolutional coding is optimal for a 16-user architecture. In the case of an 8-user architecture, the convolutional and RS codes are equal.

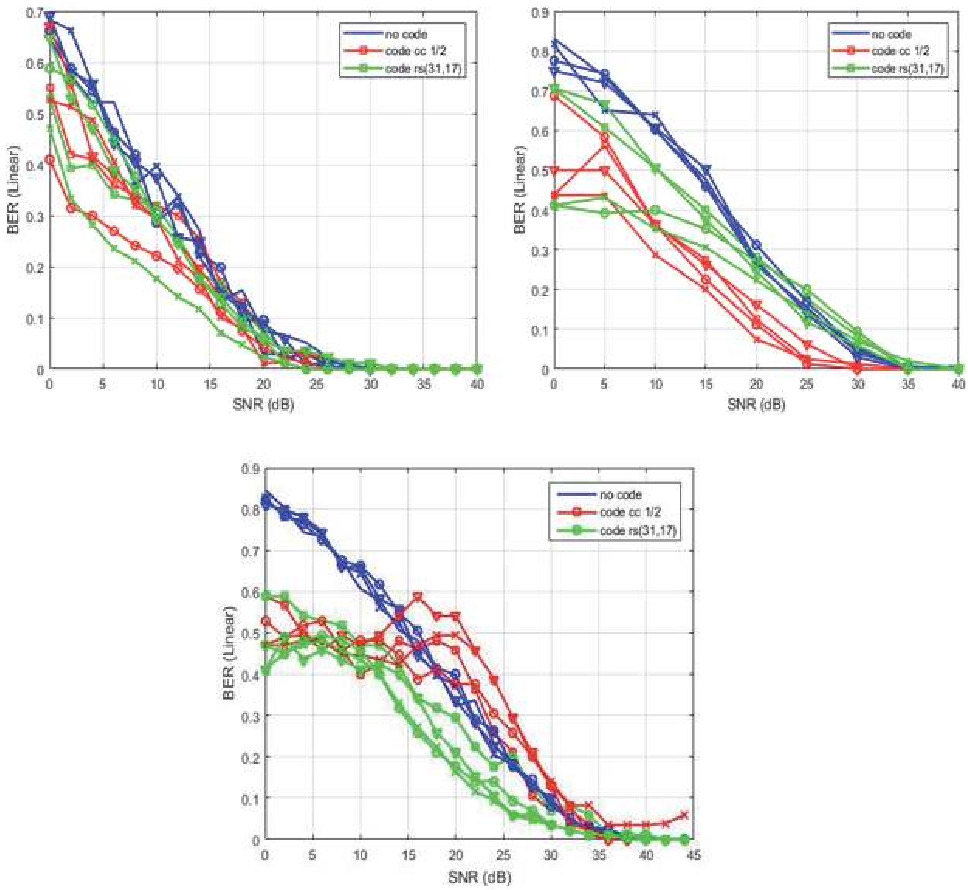

Figure 20.
BER/SNR on a fading channel with industrial noise for MTO mode.

	Number of sensors	No code	Convolutional code 1/2	RS (31,17)
Fading channel with AWGN noise	8	14 dB	12 dB	12 dB
	16	12 dB	14 dB	14 dB
	32	14 dB	12 dB	10 dB
Fading channel with industrial noise	8	20 dB	18 dB	18 dB
	16	28 dB	20 dB	26 dB
	32	30 dB	28 dB	25 dB

Table 1.
System parameters with coding.

7. Conclusion

A robust IIoT multi-user architecture based on IDWPT in transmitter and DWPT in receiver under an industrial channel has been presented in this chapter. The industrial channel was modeled as a fading channel affected by impulse noise combined with AWGN. The wireless sensor network architecture presented, with its two communication modes MtO and OtM, provides better data reception results for a noisy industrial environment. The robustness of the architecture can be improved by using channel coding or industrial noise thresholding at reception. By using a conventional error correction code with a rate of 1/4, the robustness of the MtO mode has been greatly improved and all signals are fully decoded from an 8 dB SNR on a fading channel. In MtO mode, signals are decoded from 6 dB on the same channel. Using an optimal threshold receiver, errors are eliminated by about 25 dB for MtO and OtM modes on a noisy industrial channel. As a perspective, we wish to compare the performance of the proposed architecture with the conventional OFDM communication system.

Author details

Mohamed Tabaa[2*], Safa Saadaoui[2], Mouhamad Chehaitly[1], Aamre Khalil[3], Fabrice Monteiro[3] and Abbas Dandache[3]

1 University of Montpellier, LIRMM Lab, France

2 EMSI Casablanca, LPRI Lab, Morocco

3 University of Lorraine, LGIPM Lab, France

*Address all correspondence to: med.tabaa@gmail.com

References

[1] Wollschlaeger, M.; Sauter, T.; Jasperneite, J. The future of industrial communication: Automation networks in the era of the internet of things and industry 4.0. IEEE Ind. Electron. Mag. 2017, 11, 17–27.

[2] Sasajima, H.; Ishikuma, T.; Hayashi, H. Future IIOT in process automation—Latest trends of standardization in industrial automation, IEC/TC65. In Proceedings of the 54th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE), Hangzhou, China, 28–30 July 2015; pp. 963–967.

[3] Tabaa, M., Chouri, B., Saadaoui, S., & Alami, K. (2018). Industrial communication based on modbus and node-RED. Procedia computer science, 130, 583-588.

[4] RHOLAM, Oussama, TABAA, Mohamed, et al. Smart Device for Multi-band Industrial IoT Communications. Procedia computer science, 2019, vol. 155, p. 660-665.

[5] LU, Yang. Industry 4.0: A survey on technologies, applications and open research issues. Journal of industrial information integration, 2017, vol. 6, p. 1-10.

[6] LASI, Heiner, FETTKE, Peter, KEMPER, Hans-Georg, et al. Industry 4.0. Business & information systems engineering, 2014, vol. 6, no 4, p. 239-242.

[7] Büchi, G., Cugno, M., & Castagnoli, R. (2020). Smart factory performance and Industry 4.0. Technological Forecasting and Social Change, 150, 119790.

[8] OSTERRIEDER, Philipp, BUDDE, Lukas, et FRIEDLI, Thomas. The smart factory as a key construct of industry 4.0: A systematic literature review. International Journal of Production Economics, 2020, vol. 221, p. 107476.

[9] Skobelev, P. O., and S. Yu Borovik. "On the way from Industry 4.0 to Industry 5.0: From digital manufacturing to digital society." Industry 4.0 2.6 (2017): 307-311.

[10] ZHU, Chunsheng, LEUNG, Victor CM, SHU, Lei, *et al.* Green internet of things for smart world. *IEEE access*, 2015, vol. 3, p. 2151-2162.

[11] ZHANG, Chaofeng, DONG, Mianxiong, et OTA, Kaoru. Enabling Computational Intelligence for Green Internet of Things: Data-Driven Adaptation in LPWA Networking. *IEEE Computational Intelligence Magazine*, 2020, vol. 15, no 1, p. 32-43.

[12] Sisinni, E., Saifullah, A., Han, S., Jennehag, U., & Gidlund, M. (2018). Industrial internet of things: Challenges, opportunities, and directions. *IEEE Transactions on Industrial Informatics*, *14* (11), 4724-4734.

[13] Younan, M., Houssein, E. H., Elhoseny, M., & Ali, A. A. (2020). Challenges and recommended technologies for the industrial internet of things: A comprehensive review. *Measurement*, *151*, 107198.

[14] R.W. Gao, R. Yan, "Wavelets theory and applications for manufacturing", Springer, 2011, ISBN: 978-1-4419-1544-3.

[15] Daubechies, I. Ten Lectures on Wavelets; Society for Industrial and Applied Mathematics: Philadelphia, PA, USA, 1992; 357p.

[16] Mallat, S. A Wavelet Tour of Signal Processing; Academic Press: Cambridge, MA, USA, 1989.

[17] Tabaa, M. A novel transceiver architecture based on wavelet packet

modulation for UWB-IR WSN applications. Wirel. Sens. Netw. 2016, 8, 191–209.

[18] Lakshmanan, M.K.; Nikookar, H. A review of wavelets for digital wireless communication. Wirel. Pers. Commun. 2006, 37, 387–420.

[19] Sauter, T. The three generations of field-level networks—Evolution and compatibility issues. IEEE Trans. Ind. Electron. 2010, 57, 3585–3595.

[20] Shan, Q.; Bhatti, S.; Glover, I.A.; Atkinson, R.; Portugues, I.E.; Moore, P. J.; Rutherford, R. Characteristics of impulsive noise in electricity substations. In Proceedings of the 2009 17th European Signal Processing Conference, Glasgow, UK, 24–28 August 2009; pp. 2136–2140.

[21] Sexton, D.; Mahony, M.; Lapinski, M. Radio channel quality in industrial wireless sensor networks. In Proceedings of the 2005 Sensors for Industry Conference, Houston, TX, USA, 8–10 February 2005; pp. 88–94.

[22] Luo, S.; Polu, N.; Chen, Z.; Slipp, J. RF channel modeling of a WSN testbed for industrial environment. In Proceedings of the 2011 IEEE Radio and Wireless Symposium, Phoenix, AZ, USA, 16–19 January 2011; pp. 375–378.

[23] Saleh, A.A.M.; Valenzuela, R. A statistical model for indoor multipath propagation. IEEE J. Sel. Areas Commun. 1987, 5, 128–137.

[24] Karedal, J. A measurement-based statistical model for industrial ultra-wideband channels. IEEE Trans. Wirel. Commun. 2007, 6, 8.

[25] Cheffena, M. Industrial wireless sensor networks: Channel modeling and performance evaluation. EURASIP J. Wirel. Commun. Netw. 2012, 297, 1–8.

[26] Cheffena, M. Propagation channel characteristics of industrial wireless sensor networks [wireless corner]. IEEE Antennas Propag. Mag. 2016, 58, 66–73.

[27] Saadaoui, S., Tabaa, M., Monteiro, F., Chehaitly, M., & Dandache, A. (2019). Discrete Wavelet Packet Transform-Based Industrial Digital Wireless Communication Systems. Information, 10(3), 104.

[28] Li, L. Energy-Efficient Design and Implementation of Turbo Codes for Wireless Sensor Network. Ph.D. Thesis, University of Southampton, Southampton, UK, 2012.

[29] Schmidt, D.; Berning, M.; Wehn, N. Error correction in single-hop wireless sensor networks: A case study. In Proceedings of the Conference on Design, Automation and Test, Nice, France, 20–24 April 2009; pp. 1296–1301.

[30] Oh, H.; Nam, H.; Park, S. Adaptive threshold blanker in an impulsive noise environment. IEEE Trans. Electromagn. Compat. 2014, 56, 1045–1052.

[31] Hakimi, S.; Hodtani, G.A. Generalized maximum correntropy detector for non-Gaussian environments. Int. J. Adapt. Control Signal Process. 2018, 32, 83–97.

[32] Khalil, A., Saadoui, S., Tabaa, M., Chehaitly, M., Monteiro, F., Oukaira, A., & Dandache, A. (2019). Combined Reed-Solomon and Convolutional codes for IWSN based on IDWPT/DWPT Architecture. Procedia Computer Science, 155, 666-671.

[33] Saadaoui, S., Khalil, A., Tabaa, M., Chehaitly, M., Monteiro, F., & Dandache, A. (2020). Improved many-to-one architecture based on discrete wavelet packet transform for industrial IoT applications using channel coding. Journal of Ambient Intelligence and Humanized Computing, 1-9.