Service Migrations in TSCH Network using Wireless Channel Estimation and Prediction

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Abstract: Industrial Wireless Sensors and Actuators Networks (IWSANs) are gateway to the Industrial 4.0, which promises to realize smart factory leading to the Industrial Internet of Things (IIoT). It employs Cyber-Physical Systems (CPSs) to enhance operational efficiency and flexibility while reducing cost. IWSANs are delay-sensitive and always require low latency and reliable connection from sensor to actuator to successfully perform a physical action. Reliability and low-latency complement each other to prevent expected failures in wireless medium. In this way, detecting and predicting failure before it actually occurs is key to actually avoid it well in time. Detection and predictions are imperative in locating faults and failures. The causes of failures in a sensor or actuator can include hardware malfunction, poor battery life, interference, accident, and short term wireless connectivity problems. Although, industrial environment mostly undertakes redundant resource to circumvent such issues, yet poor coordination among multiple resources and inaccurately predicting failures may result in losses. In such a scenario, migration of services come to be a rescue, where an intermediary can migrate service from one device, which cannot complete a task due to resource exhaustion, to a more resource-rich device.

Thus, in this paper, we focus on wireless connectivity failures caused by interference in the 2.4GHz frequency band. We do it by designing an Multi Channel Sniffing Setup (MCSS) testbed, that acts as a spectrum observer and is deployed in different locations in industrial WSAN. Alongside, we use the concept of Cognitive Radio (CR) to predict interference and noise level in the spectrum by proposing an Intelligent Low-power Wireless Spectrum Prediction (ILPWSP) based on Deep Q Network (DQN). The MCSS testbed and the ILPWSP coordinate in assessing wireless connectivity risks, predict failures in sensor and actuator nodes and then make efficient decisions on the migration of services from one device to another device. Our results show the feasibility of spectrum prediction with an acceptable ratio for reliable IWSN.

Keywords: IWSAN; TSCH; Channel Prediction; Migration service

1 Introduction

The proliferation of low-cost processors along with low-power wireless technologies and advancement in the production of small high-performance microprocessors have enabled the Internet of Things (IoT) [Bl10; Gü09; Ni18]. It is predicted that the number of devices connected to the Internet will increase by 75 billion devices [Na18], by 2025. It includes

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applications such as smart homes, smart cities, and smart factories. Each application has its unique Quality of Service (QoS) requirements. For example, while video surveillance requires high-throughput, timeliness is critical in applications such as autonomous driving to avoid a fatal accident. Industry 4.0 is one of the main domains benefiting from IoT by employing Cyber-Physical Systems (CPSs). It is predicted that by 2026, the worldwide market for industrial wireless will reach 7 Billion dollars. Furthermore, over 3 million robots will operate in industries by 2020. In some cases, robots and actuators will be responsible for a critical task that has to be executed in real-time. According to International Society of Automation (ISA) based on the QoS requirements three categories are defined. Fig. 1 explains the importance of timeliness in safety and control applications. Because wired networks suffer from issues such as scalability, mobility, and high cost, there is a need for reliable wireless solutions to guarantee low-cost, flexibility, and packet delivery in real-time.

Category	Class	Application	Description
Safety	0	Emergency action	Always critical
Control	1	Closed-loop regulatory control	Often critical
	2	Closed-loop supervisory control	Usually non-critical
	3	Open-loop control	Human in loop
Monitoring	4	Alerting	Short-term operational consequence
	5	Logging and downloading/uploading	No immediate operational consequence

TSCH

IEEE 802.15.4

Increasing timeliness requirement

Fig. 1: Different classes of industrial applications defined by ISA

Despite such benefits, wireless solutions need to be energy efficient as the sensor/actuator nodes are battery-powered. Because radio is the major cause of energy consumption in IoT devices. An extended radio operation time will reduce battery life, thus an unexpected death of nodes will harm network reliability. Medium Access Control (MAC) protocols are designed to manage and schedule wireless communication, but the static nature of MAC protocols fail to predict a highly dynamic wireless spectrum.

In this regard, an efficient protocol called Time-Slotted Channel Hopping (TSCH) has been proposed as part of the IEEE 802.15.4 standard, which dynamically involves channel hopping to overcome channel impairments such as interference and fading. However, such random channel hopping still suffers from dynamic channel conditions at different transmission times and locations, which makes some nodes highly prone to transmission failures at one location while other nodes having a higher likelihood of transmission success at a different location. In many cases, it can be beneficial to assign the task of another sensor/actuator nodes, who can not complete their task optimally, and then reassign the same task to nodes who are more capable. This can be achieved by migrating the code to another device with similar resources and adopting its functionality to the task requirements. Failure in Industrial Wireless Sensors and Actuators Networks (IWSANs) can be due to many reasons such as defected parts, accidents, or poor network connectivity.

In this work, we focus on the lack of a reliable wireless connection because of interference in an operational location. Most of the time, the industrial environment is harsh for wireless transmissions due to the operation of various wireless networks such as surveillance cameras and Wi-Fi access points, as they may cause major interference for Industrial Wireless Sensor

Networks (IWSNs). Interference may cause a node to fail its transmission, and this not only wastes energy for re-transmission but also causes increased latency which may be a threat to real-time operation for IWSNs applications. In such cases, migration of service can play a major role, in which the case at a neighboring distance, a device with similar capability might be available to provide the same services whose interference level is lower. In this way, service migration can ensure that the entire system works reliably and with optimal resource usage. However, decision making an important part of the migration of services. The system has to compute the cost of migration based on application requirements such as latency, energy efficiency, and reliability in wireless transmission. In addition, in real-time networks, failure needs to be predicted intelligently to meet the task deadline constraints. Accuracy in interference prediction is critical to decide if because of connectivity conditions, the device is capable to accomplish the task or not. In such cases, we witness the use of Cognitive Radio (CR) to observe, learn, predict, and provide link quality estimations.

To this end, many researchers have suggested embedding machine learning in network design. Consequently, with the integration of Software-Defined Radio (SDR) and machine learning, CR algorithms are developed to control network parameters intelligently. The idea is to have a cycle of sensing, learning, and decision making by considering the consequence of decided actions as feedback for the learning process. However, training of algorithms in machine learning is an extremely time-consuming process, which makes it an undesirable solution for time-sensitive wireless networks. Approaches, such as cloud radio, are proposed to overcome this limitation by handing over the process to powerful servers located in the cloud. But even then, because of communication distance between the cloud and wireless transceivers, there is a significant delay in exchanging data. Recently, intermediary solutions such as fog and edge computing are proposed to fulfill the latency gap. Still, due to freshness of advancement in designing high power processing units (i.e., GPU) on single board computers and complexity of implementation of lightweight (i.e., energy-efficient and low bandwidth occupancy), knowledge transfer from the end node to fog server is missing.

In this paper, we develop a Intelligent Low-power Wireless Spectrum Prediction (ILPWSP) model based on *Q-learning* algorithm to predict the interference in the wireless spectrum. To provide the training data set for ILPWSP, we design a Multi Channel Sniffing Setup (MCSS) to sense the wireless spectrum concurrently and constantly. Consequently, the network manager will have real-time information about the interference in each location and it can determine the high-risk neighborhood for wireless transmission in terms of packet loss. Packet loss risk identification helps the network manager to migrate the service to the less risky location by assigning the task to a device with similar capability and resources. In this way, it can potentially increase the chance of successful transmission at a new node and location. Our results show that using ILPWSP we can achieve a reliable degree of accuracy in noise prediction in the wireless channel.

The rest of the paper is organized as follows. A brief overview and introduction is given in Section 2. The methodology of research is explained in Section 3. Section 4 presents results and finally, we conclude the paper in Section 5.

2 Background

Real-time wireless communication in IWSAN: IWSANs are the integral parts of the industry ecosystem, they could be deployed in many industrial applications resulting in concepts like CPSs, smart factory, etc. IWSANs integrates sensor networks as well as actuator networks, they complement each other in sensing and then performing required actions. This sensor-actor integration helps achieve the autonomy of many industrial processes and control systems which results in less human intervention. A rising trend of using IWSANs is seen owing to the compelling benefits of wireless networks such as low-cost of deployment and maintenance, and the flexibility and self-organizing features of sensors and actuators networks. The communication between sensors and actuators require reliable transmission of data to successfully support a mission-critical industrial application. Often such reliability is compromised due to wireless channel impairments like fading, interference, collisions, and noise. Industrial applications inherently require low-delay (real-time) and high reliability, otherwise, a successful transmission from the sensor to the actuator is difficult to maintain. Further, the industrial environment is harsh owing to the presence of heavy machinery, high-temperature conditions, high voltage induction, electrical motors, and drives operating at high voltage. Alongside this, there could be other wireless networks operating in the unlicensed 2.4 GHz spectrum. Such an environment could pose threats to reliable communication for IWSANs and hence it may compromise on the required QoS for a given industrial application. A typical scenario of wireless link failure due to the interference between an actuator and a network manager is depicted in Fig. 3(a). Mostly TSCH employs centralized network architecture, as it is widely preferred in the industrial environment due to its ease of management compared to distributed architecture [De14]. In such architecture, a network manager is responsible to assesses the overall network and takes care of the scheduling of nodes, updates the list of best channels, and selects best routes, and security measures. Employing multi-channel operation and random selection of channels instead of a single operation reduces the risk of collision because of interference. This architecture is also commercialized and used in industrial wireless network technologies such as WirelessHART. Although, channel hopping has the potential to circumvent the effects of fading and interference, yet many wireless technologies and standards share 2.4 GHz band. This sharing of the spectrum with technologies like WiFi and Bluetooth makes 2.4 GHz band crowded resulting in degrading each other's performance. Many researchers studied the impact of interference on link failure in TSCH network. For example, authors in [ZPD18] studied the cost a benefit of channel blacklisting in TSCH network. The study analyzes the local or the global implementation of channel blacklisting suggested by many researchers [Ko17]. However, the concept of channel blacklisting in TSCH is involved with the cost of delay because of channel observation and negative impact on timeliness as a result. Therefore, researchers propose the concept of CR [Mi02] using artificial intelligence and smart radio to find the interference-free time slots in the wireless spectrum. Especially with the advancement in powerful processors and lightweight machine learning algorithms, the idea of deployment of CR is becoming more practical.

Cognitive radio: Cognitive Radio (CR) in a wireless network consists of three main parts: sensing the wireless spectrum to provide a dataset that can be fed to the machine learning algorithm, a desirable machine learning model to predict interference, and making the decision to tune transmitter parameters to avoid collision and achieve required Packet Error Rate (PER). Fig. 2 shows the basic concept of CR. Below we describe important actions performed by CR.

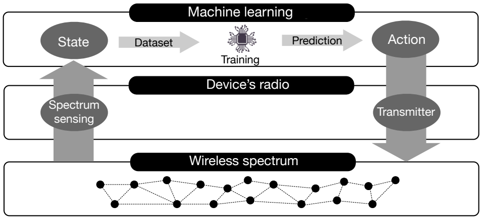

Fig. 2: The basic concept of cognitive radio for wireless network.

A) Sensing. In wireless communication and specifically, MAC layer channel sensing is an efficient approach to determine channel conditions. Generally, it is assumed that the device itself is responsible to sense channel and make transmission decisions. On one hand, this method has the advantage of higher accuracy, because the same radio in the same location is listening to the wireless channel and the interference level in the neighbor location may vary. But, this is costly in terms of power consumption due to the longer radio operation time. Cooperative and external sensing is proposed to solve this issue. In this way, wireless devices can share their observation and can have a more accurate estimation of wireless channel condition. Another benefit of this method is to assign the sensing task to devices with a constant power source to save energy for low-power devices.

B) Prediction. An optional interference prediction algorithm is critical to avoid collisions and transmission in free time slots in the spectrum. Because IEEE 802.11 has a higher data rate, transmit power, and wider channels, it is the main cause of interference in the 2.4 GHz frequency band for IEEE 802.15.4 networks. As a result, for IEEE 802.15.4 transmission in interference-free time is more desirable to save power while maintaining acceptable PER and efficiently use the shared wireless spectrum. In this direction researchers in [DT18] use Reinforcement Learning (RL) as a machine learning and prediction algorithm to optimize transmission success by decision making for channel selection in TSCH network. Sensing the spectrum helps find these interference-free gaps, however, the spectrum is very dynamic, and sensed data can lose their validity over time. In addition, to increase the accuracy of the prediction results, the machine learning algorithm demands more training samples. Low-power wireless devices are designed to save power by minimizing the radio operation and they are not capable of providing continuous high frequency sensed samples. Besides, they need to transfer these samples to more powerful computers such as fog or cloud to avoid wasting energy because of the training process. Although CR is an intelligent solution to optimize spectrum efficiency, yet in a highly crowded spectrum, it may fail to maintain a reliable connection link. Still, CR can help understand the risk of transmission on a certain wireless link. In high risky scenarios for wireless transmission, central management networks such as TSCH can assign the task to devices with a similar capability and resources placed in interference-free locations [RFG19]. This concept is called the migration of service and it is achievable using the virtualization machine to be operating system agnostic to execute any codes written for different platforms.

The need for service migration in IWSAN: In traditional IWSNs scalability is challenging because of the direct connection of the end node and cloud service. The reasons for this challenge are bandwidth limitation and response delay because of physical distance of cloud service from operational node and increasing the size of collected data to process and analyze. The concept of IoT at the edge or introducing the intermediate fog nodes helps to increase the scalability and timeliness by dis-aggregation of services.

3 Migration service architecture using MCSS testbed and ILPWSP

In our design we deploy several multi-channel sniffing devices alongside the operating nodes in IWSNs. In this case, MCSS continuously observes and monitors the interference conditions in the target location and provides feedback to the central manager. When a transmission in the location A has a high risk in terms of packet loss, the central manager can assign the task to another device in location B with similar resources. We consider a typical industrial network architecture as shown in Fig. 3, which comprises of existing architecture in Fig. 3(a) and our proposed architecture in Fig. 3(b). Industrial environments are full of wireless devices such as surveillance cameras, WiFi access points, and smartphones. The operation of these devices in the neighborhood of the industrial sensors and actuators causes interference in the wireless channel. Lack of reliable connection for real-time IWSNs may cause a severe impact on the functionality of the entire network. Our proposed solution for this problem is presented in Fig. 3(b), where we introduce the MCSS and fog radio for interference prediction. In this scenario, MCSS is continuously monitoring the wireless channels and feeding the machine learning based prediction model deployed in the fog computing.

Multi Channel Sniffing Setup (MCSS): As shown in Fig. 3(c), MCSS consists of 40 nRF52840 USB dongles, each dongle is responsible to sniff a single channel with 2MHz width in 2.4 GHz frequency band. The nRF52840 includes an ARM Cortex-M4 processor with 1MB flash memory, 256KB RAM, and has -95dBm antenna receiver sensitivity. This setup allows us to collect noise samples of all the channels with 9μs interval for major low-power wireless technologies operating in 2.4 GHz, such as different versions of Bluetooth Low Energy (BLE), IEEE 802.15.4, and 2.4 GHz proprietary protocols. The observation provides real-time feedback about the noise in wireless spectrum in a defined location. Using the collected dataset ILPWSP can predict the channel condition in the future. ILPWSP helps to reduce the risk or PER caused by interference, by assigning the task to

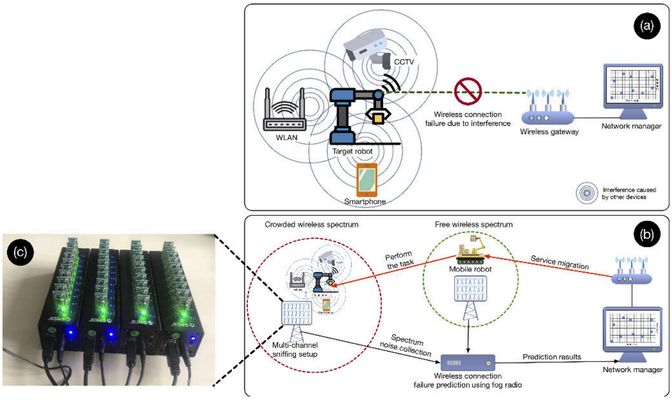

Fig. 3: The proposed network scenario

other devices with similar resources and capability. The output recorded by this tested setup is fed to the fog radio.

Intelligent Low-power Wireless Spectrum Prediction (ILPWSP): Reinforcement Learning (RL) is one of the active research areas in machine learning for time series prediction. In RL, the environment, and defining adaptive policy using perceived states of the environment helps to improve the accuracy of decision making and continuous adaptation with the environment. RL is also known as a semi-supervised machine learning algorithm, because it receives feedback from its previous actions to improve accuracy over time. In the wireless spectrum, due to the high variation of interference level in a short period, RL algorithms are suitable to continuously observe and predict. The key entities in RL are *agent*, *environment*, *actions*, *rewards*, and *states*. The *agent* interacts with the *environment* and takes *action*. In return, it retrieves the *rewards* or *penalty* from the effect of previous *action* in the *environment*. This feedback helps to improve decision accuracy. In ILPWSP, the *agent*, which is our Q-learning model, interacts with the wireless spectrum environment based on the configuration parameters given through actions. In each corresponding state, the agent receives the reward based on the action. In our simulation experiments, the agent keeps track of all the errors based on the actions taken, and the rewards received, through this online learning, it generates an optimal policy to minimize those errors. The agent minimizes errors by comparing error values with the available training data set, which we feed as input to the model. In the next step, the model is validated through testing data set so as to examine if the optimal parameters selection is performed with reasonable prediction accuracy. The optimal configuration parameter is expressed as Markov Decision Process (MDP) [SB18]. Among many variants of RL, *Q-learning* is a unique approach of online learning. It arrives at a policy based on a Q-table which stores the results of actions taken from a given state. ILPWSP is based on *Q-learning* and it can navigate high dimensional configuration parameter space depending on strategy value function Q. Equation (1) explains the *Q-learning* where Q is a state-action value denoted by $Q(s_t, a_t)$ and works as follows.

Agent observes the environment and performs an action in it and aims towards maximizing the expected reward. For real-time spectrum prediction in a complex wireless environment, *Q-learning* is efficient to find out the best policy of RL based on value function. *Q-Learning* is an incremental algorithm that determines optimal policy in a step by step process at each step t, agent observes current state s_t, selects and performs an action a_t and observes the next state s_{t+1} in the process, receives reward r_t, and finally updates the Q values $Q(s_t, a_t)$.

$$Q_{t+1}\left(s_t, a_t\right) = Q_t\left(s_t, a_t\right) + \eta\left[r_t + \gamma \min_{a_t} Q_t\left(s_{t+1}, a_{t+1}\right) - Q_t\left(s_t, a_t\right)\right] \tag{1}$$

Process repeats until Q value function converges to an optimal value as $Q_{t+1}(s_t, a_t) \rightarrow Q_*(S, A)$.

In this paper, we implement ILPWSP model based on DQN network which is a variant of *Q-Learning*. The ILPWSP uses grid search method to find optimal configuration parameters such as testing and training data sizes. In ILPWSP, we limit the range of configuration parameters to batch size, epochs, hidden layer nodes, input dimension, and difference order. The batch size is the number of samples to input into the model. An epoch is defined as passing of data set forward and backward once in the whole network. Hidden layers nodes act as intermediate nodes which add weights to the inputs and perform an activation function on them to produce outputs. We pass the data set multiple times into the same neural network. We collected the interference samples in an office environment operating with IEEE 802.11 enabled APs. The samples were collected on channel 11 of IEEE 802.15.4. In the dataset, we witness non-stationary behavior in different timestamps, therefore, we need to convert the dataset to stationary series by using the difference transformation technique. The main goal of ILPWSP is to predict the interference level on channel 11 in IEEE 802.15.4 with the help of DQN, where we try to find optimal policy by tuning the available parameters. The number of steps taken is 10 as selected by the grid search.

4 Results and Discussions

In this Section, we present and discuss the interference prediction results using ILPWSP. Furthermore, we compare our results with State Action Reward State Action (SARSA) as an implemented baseline algorithm to evaluate the performance of ILPWSP.

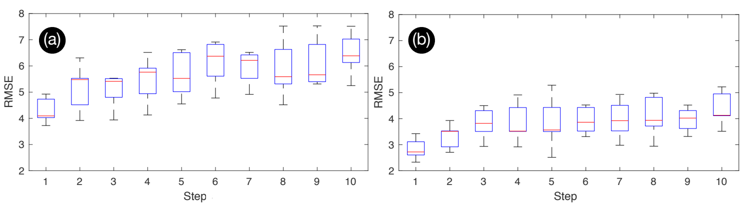

Fig. 4: (a) SARSA and (b) ILPWSP results for channel 11 in IEEE 802.15.4.

The results for the evaluation is presented in Fig. 4, where Fig. 4(a) shows the prediction results for SARSA and Fig. 4(b) demonstrates the prediction results for ILPWSP. As can be observed in the Y-axis, we use the RMSE metric to evaluate the performance of the prediction. In each part, we train and predict 0.5 million, and the samples are divided into train and test size of 0.30 and 0.20 million at each step. The optimal sample size is selected by the grid search and agent navigates through the environment and along with each step size until a terminal state. In Fig. 4(b), at the starting of the steps, the agent left free to randomly explore the environment and learning takes place by considering all possible configuration parameters of batch size, epochs, input dimension, difference order, and hidden layer node. At the second step the agent starts learning, and the error is relatively high, where the ratio of exploration is balanced and the agent by selecting all configuration parameters that result in a high error. At the third step the error has gradually decreased the agent avoided selecting the similar parameters. From the fourth step the model gradually minimize the error. At the final step, policy by the ILPWSP agent selects the optimal configuration by gaining the confidence of parameter selection and achieves low prediction error. However a detailed look at the Fig. 4(b), we notice that several trails and the number of samples length respectively the error is minimized, which determines agent selecting the right actions that result in a low error. Where in the SARSA, error increases constantly because it only considers local optimal value as the best value. While the ILPWSP follows the greedy policy. In SARSA, it takes the policy strategy into account and joins into its updates and refreshes by considering the approach of previous actions. In Fig. 4(a) shows the values of SARSA approach and concludes the result it is unable to converge the values and shows high variance. Although, in times of low interference, ILPWSP and SARSA show almost the same performance, however, when interference increases ILPWSP shows its strength over SARSA. The little differences in performance can impact the timeliness of the network and inaccuracy in the prediction which may cause collision. In this way, ILPWSP serves critical feedback that helps decide the link reliability to predict failure and efficiently make decisions of service migrations.

5 Conclusion

In this paper, we introduced ILPWSP model based on CR network for IEEE 802.15.4 to enhance the reliability and timeliness of the network. Our design is a hybrid approach that consists of three major elements: First we design a MCSS for external cooperative sensing method in CR. Second, we use fog radio to dis-aggregate the computing for machine learning in ILPWSP to achieve low latency. Last, for prediction part in ILPWSP we develop a DQN model. Our results for ILPWSP prove the feasibility of spectrum prediction for decision making to migrate the service in case of a high risk of interference.

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References

[Bl10] Blywis, B.; Güneş, M.; Juraschek, F.; Hofmann, S.: Gossip routing in wireless mesh networks. In: 21st Annual IEEE International Symposium on Personal, Indoor and Mobile Radio Communications. IEEE, pp. 1572–1577, 2010.

[De14] De Guglielmo, D.; Seghetti, A.; Anastasi, G.; Conti, M.: A performance analysis of the network formation process in IEEE 802.15. 4e TSCH wireless sensor/actuator networks. In: 2014 IEEE Symposium on Computers and Communications (ISCC). IEEE, pp. 1–6, 2014.

[DT18] Dakdouk, H.; Tarazona: Reinforcement Learning Techniques for Optimized Channel Hopping in IEEE 802.15. 4-TSCH Networks. In: Proceedings of the 21st ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems. Pp. 99–107, 2018.

[Gü09] Güneş, M.; Juraschek, F.; Blywis, B.; Mushtaq, Q.; Schiller, J.: A testbed for next generation wireless network research. PIK-Praxis der Informationsverarbeitung und Kommunikation 32/4, pp. 208–212, 2009.

[Ko17] Kotsiou, V.; Papadopoulos, G. Z.; Chatzimisios, P.; Theoleyre, F.: Label: Link-based adaptive blacklisting technique for 6tisch wireless industrial networks. In: Proceedings of the 20th ACM International Conference on Modelling, Analysis and Simulation of Wireless and Mobile Systems. Pp. 25–33, 2017.

[Mi02] Mitola, J.: Cognitive radio. An integrated agent architecture for software defined radio./, 2002.

[Na18] Nawaratne, R.; Alahakoon, D.; De Silva, D.; Chhetri, P.; Chilamkurti, N.: Self-evolving intelligent algorithms for facilitating data interoperability in IoT environments. Future Generation Computer Systems 86/, pp. 421–432, 2018.

[Ni18] Nikoukar, A.; Raza, S.; Poole, A.; Güneş, M.; Dezfouli, B.: Low-Power Wireless for the Internet of Things: Standards and Applications. IEEE Access 6/, pp. 67893–67926, 2018.

[RFG19] Raza, S.; Faheem, M.; Guenes, M.: Industrial wireless sensor and actuator networks in industry 4.0: Exploring requirements, protocols, and challenges—A MAC survey. International Journal of Communication Systems 32/15, e4074, 2019.

[SB18] Sutton, R. S.; Barto, A. G.: Reinforcement learning: An introduction. MIT press, 2018.

[ZPD18] Zorbas, D.; Papadopoulos, G. Z.; Douligeris, C.: Local or global radio channel blacklisting for ieee 802.15. 4-tsch networks? In: 2018 IEEE International Conference on Communications (ICC). IEEE, pp. 1–6, 2018.