Spectrum Coordination for Intelligent Wireless Internet of Things Networks

Zorica Nikolić, Milorad Tošić, Nenad Milošević, Valentina Nejković, Filip Jelenković

Abstract — **Diversity of radio access technologies, such as ZigBee, Bluetooth, LTE and Wi-Fi, together with growing requirements for their simultaneous use, significantly increase complexity of Internet of Things (IoT) wireless networks. A number of open challenges affect practical deployments, such as simultaneous use of multiple technologies, intelligent coordination of a subset of nodes, coexistence of different technologies using the same spectrum, efficient management of (simultaneously used) heterogeneous radio links, etc. This paper will consider Semantic Technology (ST), as a promising approach to coordination in such complex wireless infrastructures, especially in cases where interference models are not well understood. A Neural Network (NN) will be used for the network state estimation and ST for reasoning about required actions. It is based on semantic data sets mining such that coordination decisions may be driven by predictions instead of using physical spectrum sensing devices. ST facilitates reasoning about coordination, application priority, frequency selection and dynamic spectrum access. Because of capability of the NN to solve regression and classification problems, potentially problematic network states could be proactively avoided instead of reactively corrected particularly in priority critical applications.**

Keywords — **Coordination, Internet of things, semantic technologies, WiFi, ZigBee.**

I. Introduction

THE seamless blending of computers into every day's life is an idea that exists for several decades [1]. However, the integration of computers has evolved into the integration of different smart devices, such as sensors, within a large network. The growth in area sped up in the 21st century [2], with the development of the Internet and wireless technologies, creating what is now called the Internet of Things (IoT) [3], [4]. The IoT is being realized with a number of low-cost small devices, having computing capabilities, equipped with different sensors or actuators.

Because of the different environments, applications, needs, and requirements, the IoT may be divided into industrial IoT and consumer IoT [5]–[7]. Industrial IoT is characterized by machine-to-machine communication, machine learning, Big Data analysis, and mission and safety critical applications. On the other hand, consumer IoT are related to the consumer applications, such as wearables, media, home automation, smart appliances, and are characterized by low volumes and rates, and they are not safety critical, in general.

An important part of the IoT technology is the communication subsystem [8]. Due to a wide variety of communication environments and application areas, there exist a number of communication technologies. Some of these technologies are developed for the specific applications, such as ZigBee [9], [10] and Bluetooth low energy [11], [12]. On the other hand, cellular communications and WiFi are widely used for other purposes. Furthermore, new communication technologies are constantly being developed and implemented in the IoT systems. The communication subsystem evolved significantly over the years. First IoT devices, about 35 years ago, were designed around Radio Frequency IDentification (RFID) technology [13], using a relatively simple signalling. A decade later, a concept of IoT significantly improved within the wireless sensor networks [14]. These applications were very interesting for both consumer and industrial applications, and therefore they gained a noteworthy attention. This situation imposed the development of the standardized IoT framework, both by the industry or organizations that develop standards. However, the first developed standards were not compatible enough, due to lack of cooperation between the developers, and they essentially slowed down the growth of the IoT. Later the situation improved and organizations, such as 3GPP, ETSI, IEEE, provided standards that enabled seamless interconnection of different devices. Especially important is the development of IEEE 802.15.1 Bluetooth and IEEE 802.15.4 ZigBee technologies, aimed at short range low power communications. These technologies are widely used

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today, but there is one major problem. Namely, both technologies use 2.4 GHz frequency band, which is also used by IEEE 802.11 WiFi devices. In order to avoid or reduce the unwanted interference between these technologies, some sort of coordination is needed.

It was shown that ZigBee devices experience a significant packet loss in case of interference. The predominant reason for the ZigBee packet loss is the WiFi transmission power, which is much higher than that of ZigBee [15]–[17]. There are different ways to reduce or completely avoid the interference: space, time or frequency domain. Interference avoidance in the space domain is hardly applicable for ZigBee devices due to the fact that a large number of devices is deployed in a broad area. On the other hand, time domain interference avoidance may be applied for this purpose. In fact, WiFi has built-in technology to avoid other active users by sensing the presence of the carrier. However, since ZigBee has much lower transmit power than WiFi, WiFi is not able to detect it [15] regardless of the strength of the ZigBee device output signal. Authors of [18] came across an idea to use a separate transmitter, called Signaler, much stronger than ZigBee. The Signaler starts its transmission upon the detection of ZigBee transmission. WiFi detects the Signaler and stops its transmission. This approach enables ZigBee to transmit successfully, but at the cost of lower frequency usage efficiency. Another method [16] uses the fact that WiFi is not transmitting continuously, and there are gaps, called white spaces, in the transmission. ZigBee devices use these gaps to transmit its data. Each ZigBee device periodically samples the channel and predicts the length of the white space in WiFi traffic using Pareto model. It adapts the frame size to avoid the collision with WiFi transmissions. Unfortunately, in this case many ZigBee devices transmit at the same time and cause high mutual interference, and the time synchronization of the large number of ZigBee devices is difficult. These problems limit the applicability of the interference avoidance in time domain to rather small number of ZigBee devices. The frequency domain interference avoidance is also of interest. Here only one or both groups of the devices change its operating frequency. The most of the research is focused on ZigBee devices and its channel adjustment [19]–[23], but recently [24] proposed that both ZigBee and WiFi change operating frequency. Paper [19] proposes an adaptive interference-aware clustering algorithm using multiple channels in a ZigBee network in the presence of WiFi interference. The algorithm avoids interference from WiFi employing interference detection and avoidance schemes to adaptively reconfigure multiple channels in a ZigBee cluster-tree network. Distributed adaptation strategies for ZigBee nodes, to minimize the impact of the WiFi interference, are proposed in [20]. The first strategy is based on scanning, and this strategy has increased power cost. The other strategy is based on the increased cognition through learning. If learning is added to the system, it is possible to achieve 50% energy savings. Interference estimators that can be efficiently implemented on resource constrained sensor nodes using off-the-shelf radios are presented and distributed algorithms that use these estimators to dynamically switch frequencies as interference is detected are proposed in [21]. Within [22], an objective comparison of different candidate channel selection mechanisms based on a new multichannel protocol taxonomy using measurements in a real-life testbed is conducted. Paper [23] proposes an adaptive interference avoidance scheme that enhances the performance of ZigBee networks by adapting ZigBee's transmissions to measured WiFi interference. On the other hand, in [24] a cooperative channel control method is proposed, for both ZigBee and WiFi. This methodology would be used by both WiFi users and ZigBee applications in parallel. The paper shows the switching the channels of both ZigBee and WiFi signals leads to the more efficient use of the channels and to the improvement in the sink arrival rate of ZigBee packets. The satisfaction rate of the ZigBee users is increased, at a cost of slightly lower WiFi throughput.

The rest of the paper is organized as follows. Section II discusses the problem of ZigBee and WiFi coexistence. Different approaches to the spectrum coordination are explained in Section III. Sections IV and V consider neural networks (NN) with Deep Learning and Semantic Technologies (ST), respectively. Section VI presents the concept and proposes an intelligent spectrum coordination, using NN and ST. The concluding remarks are given in Section VII.

II. ZigBee WiFi Coexistence

A. ZigBee

ZigBee is a low-power and low-cost wireless network standard. It is primarily used in wireless sensor networks, which is the first application of IoT in the industry. It was proposed back in 1998 and revised two times. The second and final revision is established in 2006. ZigBee is based on IEEE 80.15.4 standard and operates in 2.4 GHz frequency band. ZigBee Physical level satisfies the needs of IoT networks. However, MAC level is shown to be unreliable with high energy consumption [25], [26]. Therefore, to overcome this problem some modifications in the MAC level are proposed in IEEE 802.15.4-2012 standard.

B. WiFi

WiFi operates according to the IEEE 802.11 standard and its subversions. Unlike ZigBee, WiFi was not designed for IoT applications. It is designed to deliver high throughput to the devices that are close to each other. The number of supported devices is not high. The main obstacle for the application of WiFi in IoT is its high energy consumption, much higher than Bluetooth or ZigBee. It was later improved regarding the energy consumption, but it is still not widely used for IoT devices.

C. Coexistence

Although WiFi is not used in IoT applications, it is still interesting for them since it causes interference to ZigBee devices. Namely, WiFi is designed to operate in both 2.4 and 5 GHz frequency bands, with 2.4 GHz band being heavily used today. Since ZigBee also uses 2.4 GHz band, mutual interference is inevitable. To understand the potential for problems, a review of the RF spectrums and available channels for WiFi (802.11b/g) and ZigBee (802.15.4) is shown in Fig. 1 [27].

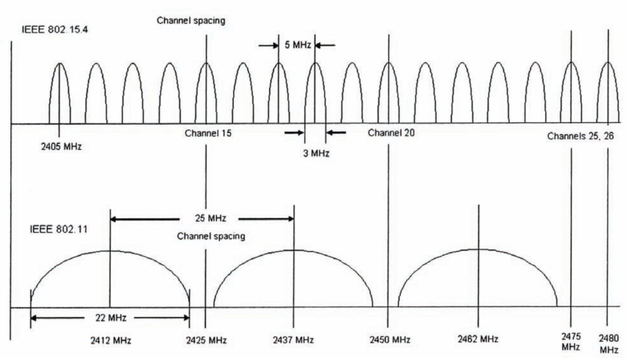

Fig. 1. Comparison of IEEE802.15.4 and IEEE802.11 spectrum occupancy.

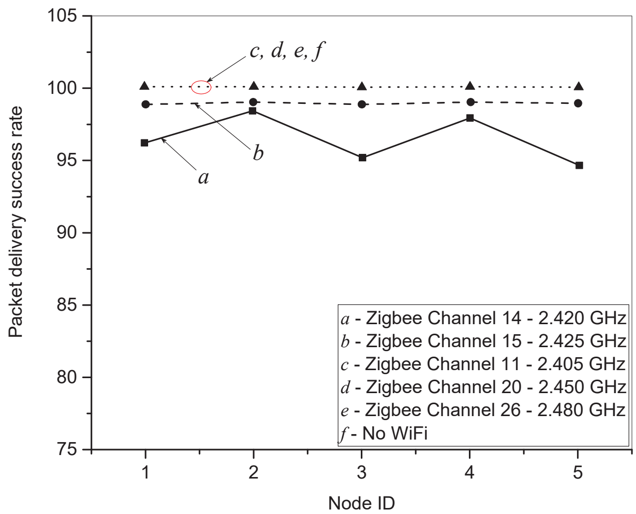

Fig. 2. ZigBee radio packet delivery success rate in the presence of standard-power WiFi station at 2.422 GHz.

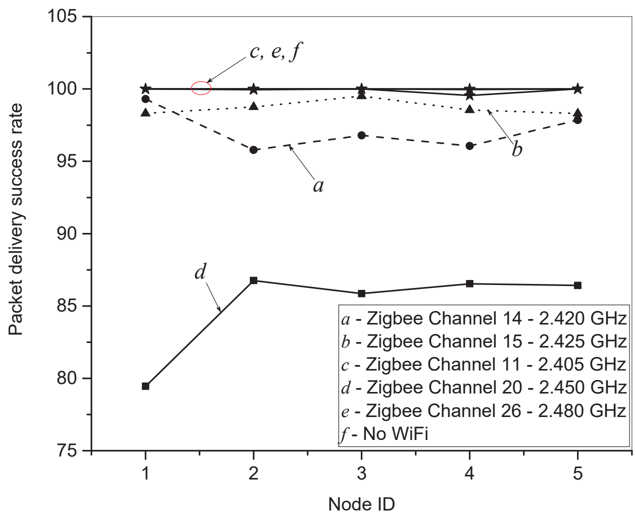

Fig. 3. ZigBee radio packet delivery success rate in the presence of high-power WiFi station at 2.422 GHz.

In the following text, the influence of WiFi on ZigBee transmission is demonstrated. In [27], the interference caused by WiFi to ZigBee network is analysed. Two different WiFi transmitters are considered: standard-power (100 mW) and high-power (200 mW). In both cases, WiFi is set to operate at a fixed WiFi channel 3 or at 2.422 GHz. Figs. 2 and 3 [27] depict the ZigBee packet delivery success rate for standard- and high-power WiFi, respectively. ZigBee nodes are at different locations (Node ID) and operate at different channels. The results show that WiFi may significantly degrade the performance of ZigBee networks, especially in case of high-power WiFi.

III. Spectrum Coordination

The coordination of the shared unlicensed spectrum is a very important task. The spectrum coordination may be generally divided into reactive and proactive spectrum coordination [28].

In the group of reactive spectrum coordination algorithms, the simplest one is agile wideband radio [29]. This algorithm consists of several steps. In the first step, the transmitter senses spectrum, the analyses it, and finally chooses the operating frequency in accordance with the highest acceptable interference intensity. Although this algorithm is very simple, it may have problems with the so called hidden nodes, i.e. with nodes that may cause interference, but they are not visible to the transmitter. The other algorithm, that overcomes the mentioned problem, is reactive control [30]. It is also a simple scheme, with a difference that all the stations in the network optimize the transmission channel quality, i.e. the desired signal and interference intensity, by controlling different parameters, such as operating channel, transmission rate or its power. The changes occur as a reaction to the observed state of the network and therefore the name *reactive*. Due to its nature, the reactive schemes are applicable only to some simple network topology cases. Proactive spectrum coordination algorithms are slightly more complex than the reactive and may operate in more complex scenarios. The spectrum etiquette protocol [31] is an illustration of the proactive algorithms. This algorithm reserves a dedicated coordination channel, which may be a separate physical radio channel or some internet service. The coordination channel is used for the exchange of the messages regarding the transmission parameters, thus optimizing the wireless channel. The Common Spectrum Coordination Channel (CSCC) [31], [32] is a variant of the etiquette approach. It demonstrated the application of the algorithm case of the 2.4 GHz band shared by WiFi and Bluetooth.

A cooperative channel control method of ZigBee and WiFi for IoT services is proposed in [24]. The proposed method controls not only ZigBee devices and channels but also requests a temporary pause in the use of specific WiFi channels. The results show that the method improves the satisfaction rate of ZigBee users, at the cost of the lower WiFi throughput, as shown in Figs. 4 and 5.

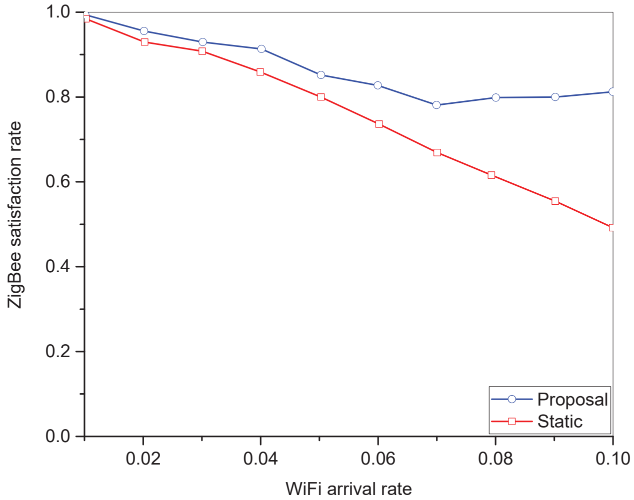

Fig. 4. ZigBee satisfaction rate as a function of WiFi arrival rate.

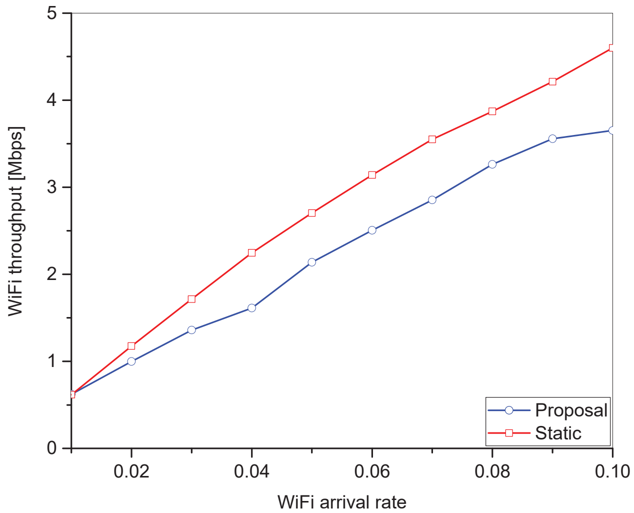

Fig. 5. WiFi throughput as a function of WiFi arrival rate.

Another promising approach to the coordination problem is to use semantic technologies and neural networks, as discussed in the following sections.

IV. Neural Networks and Deep Learning

Neural networks are compounded of neurons that are simple and connected processors. Neurons produce a sequence of activations. A NN has input neurons which get activated through sensors perceiving the environment. The rest of neurons get activated from previously activated neurons connected with them through weighted connections [33], [34]. The neuron receives one or more inputs and sums them to produce an output or activation. Edges between neurons from different layers can be assigned by weight, which are real numbers expressing the importance of the respective inputs to the output. The neuron's output can be 0 or 1 determined by whether the sum, where weight and input components are taken in calculation, is less than or greater than some threshold value. The threshold is a neuron parameter.
NN with the first layer of neurons, which are making very simple decisions by weighing the input evidence is shown in Fig. 6. In the second layer, neurons are making a decision by weighing up the results from the first layer of decision-making. A neuron in the second layer can make a decision at a more complex and more abstract level than neurons in the first layer. More complex decisions can be made by the neurons in the third layer. In this way, a many-layer network of neurons can be engaged in a sophisticated decision making. The rightmost or output layer may contain several or only one output neuron. The layers in the middle are called hidden layers.

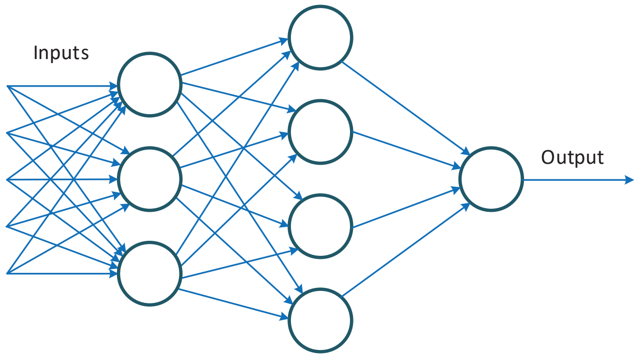

Fig. 6. Example of a simple NN.

Environment may be influenced by neurons triggering actions. Learning is about finding weights that make the NN exhibit desired behaviour. This behaviour may require long causal chains of computational stages, where each stage transforms the aggregate activation of the network. Deep Learning (DL) is learning across these stages [33], [34].
There are different model types of NNs. Models with several successive nonlinear layers of neurons are suggested at 1960s and 1970s. For example, a method for teacher-based Supervised Learning in discrete and differentiable networks of arbitrary depth called backpropagation is proposed then. It was applied in NNs in the 1981 [34], but there were difficulties in its usage in practice and had become a research theme by the early 1990s. From 2000s deep NNs become popular for alternative machine learning methods. Supervised deep NNs were used for pattern recognition and become relevant for Reinforcement Learning without supervising teacher [34]. Feedforward and recurrent NNs shown good results.
The most common uses of NNs are in following:
1) *Classification*, with dividing an *n*-dimensional space into various regions and assigning regions to classified items. The examples can be found in many real-world applications, for instance in pattern recognition. Each pattern is transformed into a multi-dimensional space, which is further classified to a certain known pattern group. Feed-forward networks are commonly used for such classifications.
2) *Prediction*, where NN can be trained to produce outputs that are expected based on a particular input. NN can predict results, such as stock market prediction. For such prediction *feed-forward networks* is usually used.
3) *Clustering*, sometimes data classification into different categories is very complicated. NNs can be used to identify special features of these data and classify them into different categories without prior knowledge of the

data. This technique is useful in data-mining. Several solutions exist regarding the type of used networks, such as Simple Competitive Networks, Adaptive Resonance Theory (ART) networks, Kohonen Self-Organizing Maps (SOM), etc.

4) *Association*, a NN can be trained to remember a number of patterns. When a distorted version of a pattern is presented, then the NN associates it with the corresponding pattern in memory and returns the original version of the pattern. This is useful for restoring noisy data or for image compression. Hopfield networks is commonly used for solving association problems.

V. Semantic Technologies

Data are relatively unstructured and random when are interpreted by human. Data can be represented by simple metadata representations using XML technology. When data is XML represented, then finding and correlating patterns in raw documents is possible. Richer metadata presentations are possible using Resource Description Framework Schema (RDFs) where we can store and connect patters via conceptual model or ontology and to link to documents to aid retrieval.

Ontologies are specified through different theses of knowledge representation. The differences among different theses of knowledge representation are based on the fact what interpretations of their model theoretic semantics contain and the way of interaction among containing components. Semantics of many knowledge representation thesis is based on interpretations. The common used thesis is RDFS, which differs from other theses in the structure of statements. RDFS represents an abstract data model that defines relationships between entities. In this thesis entity is resource in Resource Description Framework (RDF). Set of resources and anything that have a universal resource identifier (URI) in the universe can be modelled using RDF model. That can be properties and statements. Resources may be related to each other or to literal values via properties. Such a relationship represents a statement that itself may be considered a resource. The semantic consequences of the RDFS thesis include that all properties (predicates) are elements of the domain of discourse and all semantic relationships are reducible to properties. Descriptions of resources represent statements [35]. The structure of statements is subject-predicate-object structure. Predicates and objects are resources or strings. Subject and object can be anonymous objects (blank nodes), too [36].

RDFS is a very limited language, and more expressive power is needed for describing resources in sufficient detail. For example, it is useful to be able to state that a property is functional or transitive and it is extremely useful to be able to describe classes in terms of the properties of the individuals that belong to them. That descriptions are prerequisites for automated reasoning, such as determining the semantic relationship between syntactically different terms. Reasoning services use very rich metadata such as Web Ontology Language (OWL) that describe the elements semantics using more expressive constructors than RDFs. Query language for retrieving information from Web data sources is SPARQL. Reasoning services enable automatically concepts acquiring. Ontologies evolving into domain theories is possible, too.

VI. Intelligent Spectrum Coordination

Adoption of semantic technologies is a promising approach to coordination of complex wireless infrastructures, where different radio access technologies, such as ZigBee, Bluetooth, LTE and Wi-Fi, together with growing requirements for their simultaneous use, significantly increase complexity of IoT wireless networks, especially in cases where interference models are not well understood. SemantiC Coordination for intelligENT sensors (2CENTs) [37] implements network intelligence on top of the FIESTA-IoT [38] platform by adopting a NN for the network state estimation and ST for reasoning about required actions. In this way, the physical spectrum sensing devices may be replaced by the prediction, and the predicted data may be used for the spectrum coordination.

In this paper we describe a novel cloud-based semantic inter-network coordination protocol that facilitates dynamic spectrum coordination in the HetNets for efficient spectrum utilization. It is focused on coexistence between IEEE 802.15.4 and Wi-Fi technologies as dominant participants in 2.4 GHz frequency range of IoT networks. The novelty of the proposed solution lays in the adoption of NN for the estimation of HetNets channel allocation map from dynamics in collected sensor measurements data. Following the FIESTA-IoT information modelling approach, ontologies are used for knowledge representation as bases for automatic reasoning about optimal channel allocations. The ontology framework approach has been previously successfully proven in the case of LTE-U coordination [39], [40]. The proposed adoption of the framework builds upon the FIESTA-IoT domain and information models. The coordination and spectrum sensing are modelled as an interactive process, where system nodes communicate and share knowledge about relevant spectrum conditions. Coordination of the devices spectrum usage, that could be based on different radio access technologies, is centralized on the 2CENTs controller. Semantic channels are established within the system for the interaction between participating communication devices that feature FIESTA-IoT Experimentation-as-a-Service (EaaS) API.

The 2CENTs system architecture is given in Fig. 7. The semantics in the system are implemented by Knowledge Bases (KBs) and Ontologies (ONTs) where KBs store knowledge about network state, generated by the NN from the collected measurements data according to the domain knowledge accumulated in the ONTs. The Network Capability KB contains semantic descriptions of the EaaS APIs needed for generating commands that configure measurements collection. Reasoning about Network Capability is based on the Domain Ontology. Features Mapping ontology defines how collected measurements data are mapped into the set of features that are used as inputs to the NN Model. The NN Model learns about the system behaviour (Fig. 7a) and makes predictions about future system states (Fig. 7b). In this way, the 2CENTs

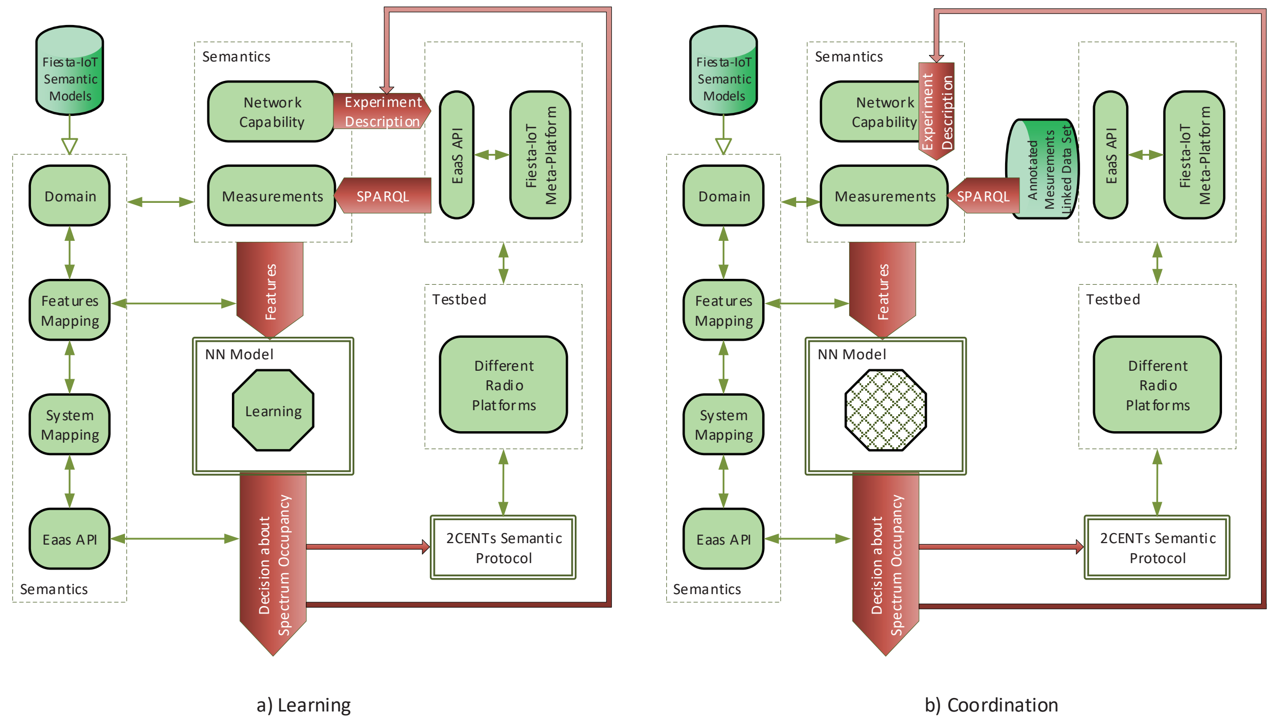

Fig. 7. 2CENTs system architecture.

controller makes proactive coordination decisions instead of waiting for a problem to happen in the system and to make corrective actions. Outputs of the NN Model are semantically interpreted by using the System Mapping ontology and used for reasoning about how to optimize results obtained from the NN into scripts of API commands.

VII. Conclusion

This paper discusses the problem of the coexistence between WiFi and ZigBee networks within the IoT applications. Some of the existing solutions control ZigBee transmission and adapt it to avoid WiFi. The others control both WiFi and ZigBee and achieve better ZigBee satisfaction rate at the cost of lower WiFi throughput. A possible solution that employs neural networks and semantic technologies is proposed in this paper. Neural network is used to predict usage patterns of ZigBee and WiFi and estimate the current network state. On the basis of these information, semantics is used for reasoning about needed coordination steps.

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