The Internet of Things for Intelligent Transportation Systems in Real Smart Cities Scenarios

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***Abstract* — This paper represents an overview on activities done in real Smart Cities scenarios using IoT Technologies for Intelligent Transportation Systems (ITS). Nowadays, there are several use cases related to IoT for ITS, such as connected and autonomous vehicles, cooperative transportation networks and smart roads in order to improve data propagation, create heterogeneous connectivity and low latency applications in high capacity environments. ITS techniques can be also applied on logistics, so accuracy on delivery and timing can be improved consider all the involved ecosystems, baseline and standardized architectures in interconnected Smart Cities for future development and integration. Secure correlations between vehicles and smart roads can optimize road safety and traffic flow, reduce incidents, avoid congestions etc. These technologies comprise also V2X (Vehicle to Everything). In this scenario, the cloud-based LoRa (Long Range) and mesh networks technologies, can play an important role for the propagation of intelligent sensed data and localization. The Smart Roads scenario is considered as one of the most attractive field in a Smart City environment. The right choice on technology, delay and frequency represents an important factor to be considered for standardization and engineering activities.**

Keywords—ITS, V2X, Smart Cities, Smart Roads, IoT, Cloud, LoRa, 6LoW, Prescriptive Maintenance, Machine Learning

I. Introduction

Intelligent Transportation Systems (ITS) can improve mobility and logistics. IoT (Internet of Things) techniques [1] applied to mobility or vehicular traffic, can introduce many benefits such as reducing the number of accidents, optimize the road traffic and avoid pollution in Smart Cities.

Several use cases can be applicable in logistics, where transport of goods on autonomous vehicles can be done in secure monitored infrastructures in order to reduce product delivery time choosing optimal routes for packages and goods destination. These use cases comprise road traffic solutions with cloud-based systems and sensors installed on road surface and/or guard rail that count, classify and detect vehicles through advanced machine learning techniques, artificial neural networks and data mining that learn and avoid congestions and accidents. The framework outperforms on high density corridors where the secure road side unit (RSU) enable an enhanced way to forward packets to the network through low latency algorithms that prevent unexpected accidents and enable a priority and secure route through VPN (Virtual Private Network) tunneling.

The infrastructure monitoring that includes inclinometers and probes (i.e. for humidity, water on the road surface, etc.) can enable prescriptive maintenance and alert driver or autonomous car for event-based driving. Predictions and prescriptions can be done in a real-time fashion, considering heterogeneous networks in a homogeneous environment plus standardized metrics that compared with the sensed ones ensure zero error on the measurement. In this scenario, prescriptive maintenance is an increasing sector for smart cities, it consists on a trained artificial intelligence network that monitors and detects anomalies to recognize how and when an anomaly may occur. Machine learning plays a fundamental role in these kind of algorithms that represents the natural evolution of predictive algorithms. Several activities should be planned to optimize algorithms and techniques enabling new high value services.

The communication protocols adopted for these purposes are mainly wireless, due to several emerging solutions that allow to improve the performance of radio connections even in harsh environment, non-optimal conditions and long distances. The main wireless technologies proposed for real Smart Cities scenarios for ITS are: LoRaWAN (Long Range Wide Area Network) long range and battery saver, mesh networks for extend wireless coverage and protocols related to the 6LoWs (IPv6 over Low Power Network) family, WLAN-based IEEE 802.11p for V2V (Vehicle to Vehicle) and V2I (Vehicle to Infrastructure) [2]. These components can be used in a real Smart Cities environment where smart roads and connected intelligent vehicles can play a crucial role. The goal is therefore to create networks that integrate the various components and manage the information coming from IoT based sensors towards intelligent transportation systems (ITS).

The sections of this paper are structured as follows, in section 2 the main IoT communication protocols proposed for ITS and Smart Roads in Smart Cities are showed, with a particular focus on LoRa and how this technology can be used for a more accurate devices localization, 6LoW technologies for mesh networks, IEEE 802.11 for V2V and V2I. Section 3 shows the applicable machine learning algorithms and how they can improve efficiency in real scenarios. Finally Section 4 shows a reference architectures and a table that summarize several ITS use cases related to real smart cities scenarios.

II. Communication Technologies for ITS

In this section the main communication technologies adopted for V2X communication, 6Low and LoRaWAN will be discussed. The main operating characteristics are showed with their pros and cons. Furthermore, a focus on devices localization is given, evaluating how the introduced technologies could improve the current state of art.

A. IEEE 802.11p

The IEEE 802.11 standard is one of the main protocols adopted in wireless communications.

In order to meet the communications requirements between vehicles (V2V) and between vehicles and infrastructures (V2I), in 1992 the DSRC (Dedicated Short Range Communications) protocol [2] was introduced for ITS low and medium-range communications in a band of amplitude around 75 MHz to 5.9 GHz (5.850-5.925 GHz) divided into 7 channels of 10 MHz amplitude for each one. Most of these channels are accessible to individual users, but there are some reserved such as the CCH (Control Channel) reserved only for security communications and the last two channels at the end of the dedicated portion of the spectrum, reserved for future developments. With these physical layer specifications, the signal is optimal for vehicular communications, and allows further propagation in case of several multipath inside a smart city, such as vehicles, building, etc. [3].

For adapt the DSRC to the existing IEEE 802.11a infrastructure, in 2004 the WAVE (Wireless Access in Vehicular Environments) amendment was introduced. One of the substantial changes introduced is IEEE 802.11 MAC layer optimization for high-speed and low latency communications with potential safety contents, typical of ITS communications. In particular, the association procedure prior to the communication of a node to its own BSS (Base Service Set) is simplified. Some variants of these are introduced, called WBSS, that is WAVE BSS, which allow a node to communicate after receiving only one signaling message, i.e. considering a compatible BSS, it is possible for each node to receive or transmit a message without belonging to a specific BSS.

The reference architecture is showed in [4]. IEEE 802.11p is mainly associated to the PHY and MAC layers. The highest layers are managed by the IEEE 1609.x standards family.

B. IEEE 1609.x standards

As seen in [3], the IEEE 1609.x standards deal extending WAVE to the higher layers, with the IEEE 802.11p standard as a reference for the lower layers as seen above. IEEE 1609.x consists of 4 standards that define the architecture, the communication model, even in contexts where safety and the offered services at transport layer are required:

a) IEEE 1609.1 is the reference standard for the APP layer, regulates the interfaces and resources to be used and the messages format

b) IEEE 1609.2 defines the safety messages format and when they must be used

c) IEEE 1609.3 regulates the transport and network layer through the WSMP (WAVE Short Messages Protocol)

d) IEEE 1609.4 deals with providing further processing to MAC 802.11 in order to operate according to WAVE and offers an abstraction of the physical layer at the higher layers.

C. LoRaWAN

LoRa stands for Long Range and addresses long-distance wireless modulation technology with low battery consumption. For these reasons, this protocol is often used in the IoT field and therefore in ITS for Smart Roads in Smart Cities mainly. Being a low power technology, it's composed by FSK (Frequency Shift Keying) modulation at PHY layer that guarantees efficiency and low consumption, with chirp spread spectrum that allows to improve the communication range while maintaining the characteristics of a traditional FSK. These PHY layer features are extended to higher layers by LoRaWAN standard that establishes communication protocols, system architecture and network for Low Power Wide Area Network (LPWAN).

LoRaWAN technology provides bidirectional communication and star of stars topology. The topology choice is justified by the possibility of long range communications, moreover one or more gateways can be reached by a node. In fact, within a LoRaWAN network each node is not associated with a specific gateway, so multiple gateways can receive the same information transmitted by a single node.

The main components of a typical LoRaWAN network are the following:

1) End nodes: sensors or actuators that exchange compatible data with LoRaWAN technology to gateways;

2) Gateway: collect and forward the information from the various sensors and send them to the Network Server through the backhaul following a cloud based approach. Gateway can be set as packet-forwarder and/or LoRa Gateway Bridge;

3) Network Server: provides intelligence to the network, typically manages the received data and eliminates any redundancy;

4) Application Server: they are connected to the Network Servers through TCP / IP connections and allow access to the LoRaWAN network to the end users;

5) Geolocation Solver: communicates with Application Server and Network Server and provides positional information.

In order to keep energy consumption low and increase potential network scalability, the data rate management is optimized through configurable up links and down links. End nodes in a network can be heterogeneous, so they can be implemented to belong to different classes. Each class differs from the others for the management of the down link and up-link, in order to create versatile devices adapted to different application needs. There are 3 devices classes:

1) Class A: each device up link is followed by two down links chosen by each end node in an autonomous way, the most constrained devices belong to this class;

2) Class B: in addition to what standardized for class A devices, in this class there are over time extra scheduled down link slots;

3) Class C: devices belonging to this category always keep the downlink window active, inactivating it during the uplink phase, clearly this class is the most complex in terms of energy consumption.

The wasted power therefore change according to the belonging class. There are also some PHY parameters to consider, for example the spreading factor, that is the ratio between number of chip per second and symbol rate. As shown in [5], with increasing spreading factor and with the same distance, the output power decreases.

In addition to the already listed features, an important application of LoRaWAN is geolocation.

In fact, the current GPS (Global Positioning System) technology is potentially inadequate in particular contexts for IoT LPWANs application in Smart Cities for indoor and outdoor localization, where the energy saving is one of the main problems in the communication phase. One of the choice of using LoRaWAN as an alternative protocol for low power devices geolocation is the greater bandwidth than other IoT LPWANs technologies.

In [6] there is an example of geolocation implementation using LoRaWAN and an analysis of the main localization techniques for this kind of networks.

In order to estimate the position of a node, a localization technique called multilateration is usually used, which consists in locating a device calculating the different energy waves arrival time, typically RF with known propagation speed, from a transmitter source to one or more receivers. The difference between the various signal arrival times is typically indicated by TDOA (Time Difference of Arrivals). This localization is only possible if the signal transmitted by the source is received by three or more receivers. For these reasons, LoRaWAN is able to satisfy the requests necessary to provide a multilateration localization.

One of the reference LoRa localization architecture is seen in [7], where each gateway receives simultaneously the same synchronization uplink message from an end node and determines its location with the principle of multilateration. Moreover, thanks to its intrinsic properties, the LoRa signal at PHY level is able to easily overcome obstacles, making it suitable for potential indoor localization.

LoRaWAN geolocation is influenced by several factors that determine its accuracy, such as the sensitivity of each gateway's clock, the problem of multi-path in environments where there are obstacles between the source and the destination of the signal [8], gateway density in reference area, the position algorithm used by Geolocation Solver and placement of gateways and end-devices. The optimization of these factors is therefore necessary in order to improve the accuracy of the positioning. A practical use case can be imaging overlapping and machine learning techniques applied to improve localization.

D. 6LoW

6LoWs is a family of protocols that adapt IPv6 addressing to contexts where this addressing mode is not present natively.

An example is 6LoWPAN, that is a communication protocol used within wireless personal area networks. The main purpose of the latter is to carry out a link between the IPv6 addressing and the IEEE 802.15.4 standard which precisely defines the PHY and MAC layers of the WPANs.

Considering the characteristics of the devices belonging to WPANs, IPv4 addressing can be very consuming for such devices. 6LoWPAN breaks down these barriers by providing ad hoc optimization for constrained devices. It can be considered as an intermediate layer within the IEEE 802.15.4 stack that is interposed between the MAC and IPv6 layers, which provides a compression of the latter to make it more efficient at the underlying layers.

The main optimization concerns the compression of the IPv6 header by reducing the redundancy of some elements that can be deduced from the link layer.

In ITS field, 6LoWPAN [9] can be one of the main technologies for smart roads where sensor nodes in high density network are connected to other components of the network exchanging intelligent vehicle data.

III. Machine Learning Techniques for ITS

Machine Learning (ML) techniques is also a way to optimize and create powerful and advanced ITS. Its main scope is to extract patterns from a set of data and based on a specific event to make decisions independently.

Future ITS environments are going to be always richer of these ML algorithms, especially regarding autonomous driving, which according to some forecasts, will reach a level of reliability higher to human driving in 2030 [10].

In addition to autonomous driving, Machine Learning algorithms are often applied to connected vehicles that are human-driven vehicles that exchange information with a smart sensor network. There are several applications of Machine Learning to Intelligent Transportation Systems such as smart management of a traffic intersection via a sensor network [11], pedestrian and accident detection [12] [13].

Machine learning techniques widely used in this field are object recognition and prescriptive maintenance.

The first consists in detecting and recognizing objects of different nature, from the vehicle to a pedestrian to a simple obstacle. This is implemented using ad-hoc deep neural networks, that have multiple levels of complexity, called CNN (Convolutional Neural Network) [14]. The input of these networks are an image with relative label of the expected output. The image is first subjected to a convolution operation, which consists in submitting it to filtering in which certain features will be extracted.

Therefore, the convolution output is subjected to an activation function, usually non-linear, which only allows to some extracted feature being transported to the following layers.

This process is repeated for a number of times defined in the design phase of the neural network. The more layer are present, the more accuracy is obtained on output result.

At this point, after various pooling operations, the result is submitted to the fully connected layers, which will provide the final result, which corresponds to the prediction of the image content.

The second ML techniques, prescriptive maintenance is an evolution of predictive algorithms, or those classes of algorithms that aim to detect anomalies or predict specific behaviors. Prescriptive maintenance not only predicts, but is also able to independently establish certain actions when they occurs in case of an event and / or an anomaly. A similar algorithm can be composed by two sub-modules of machine learning that cooperate with each other.

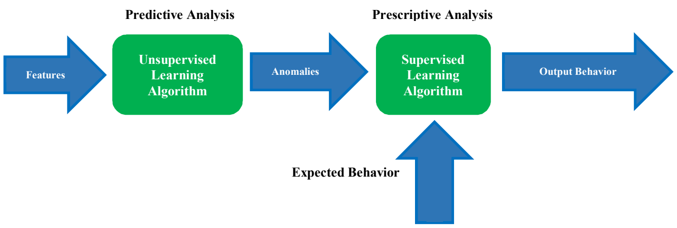

Fig. 1. Prescriptive maintenance algorithm schema.

The first performs an unsupervised learning on input features by detecting the anomaly. The latter is a supervised learning algorithm, for example an SVM (Support Vector Machine) classifier [15], which is trained on the basis of the anomaly and the correlated target behavior to ensure that the expected result is obtained. Figure 1 shows a block diagram for prescriptive analysis and maintenance.

IV. Real Smart Cities Scenarios and Smart Roads

Real Smart cities scenarios can follow the architecture represented in Figure 2. In this context, the higher levels provide a representation of information obtained from the lowest levels, including data statistics. About lower layer, special attention should be done on InfoBroker and IAM (Identity Access Manager) layers. The first collects managed information from multiple data sources and applies several security control, such as end-to-end encryption of transmitted data, information decentralization and many other user's security improvements like authentication and location privacy. The second one creates user roles and manage them providing data integrity protection and avoiding potentially attacks like Sybil [16].

This architecture can be the reference of further future developments on Smart Cities WG. In this context, smart roads cover a strategic role towards the development of advanced Intelligent Transportation Systems (ITS) powered by the Internet of Things (IoT) technologies.

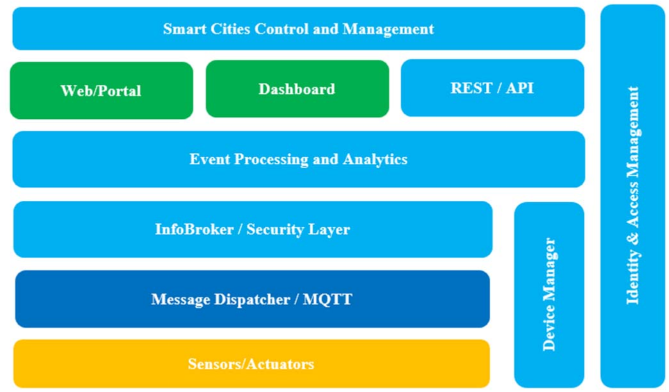

Fig 2. Smart Cities Architecture.

Focusing on Smart Roads, as depicted in Figure 3, the data flow can be represented with three main blocks.

The first block collects information from sensors of various categories such as in-vehicle data, environmental models and traffic monitoring.

The second block process the information with AI (Artificial Intelligence) techniques or with RF (Radio Frequency) based measurements.

The latter block provides the outputs for a smart city control center or connected vehicles considering the intelligence provided by the previous blocks.

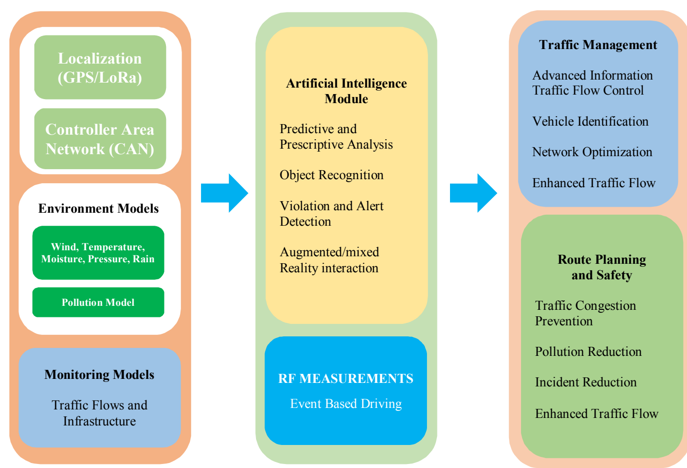

Fig 3. Smart Roads Data Flow in Smart Cities Scenarios.

A sensor network for real smart road is considered using the communication protocols discussed in the previous sections, sends and receives information from vehicles in a V2X (Vehicle to Everything) context.

Table 1 shows the main requirements classified according to the type of some environments and applications already available in such a context.

TABLE I. INTELLIGENT SMART ROADS SENSORS PARAMETERS IN REAL SMART CITIES SCENARIOS

	Variable	*Frequency*	*Protocols*	*Delay*
Road surface	Temperature, humidity, weigh in motion	Event based, min two times a day	LoRaWAN /IEEE 802.11/6LoW	≥100 ms
Road barriers	Vibration, vehicle distances	Event based, min two times a day	LoRaWAN /802.11/6LoW	≥100 ms
Bridge	Vibrations, inclinations, movements	Event based, min two times a day	IEEE 802.15.4 /LoRaWAN /6LoW	≤200ms
Tunnel	Pressure, movements	Event based, min two times a day	IEEE 802.15.4 /LoRaWAN /6LoW	≤200ms
Environment	Noise levels, CO, CO_2, NO, NO_2, brightness	Event based, min two times a day	IEEE 802.15.4 /LoRaWAN /6LoW	≤500ms
Parking Area	Vehicle counting, Parking Slots availability	Event based, min two times a day	IEEE 802.15.4 /802.11 /LoRaWAN	≤200ms
Road Works	Geolocation Management	Event based, min two times a day	IEEE 802.15.4 /802.11 /LoRaWAN /6LoW	≤1ms
Traffic flow	Traffic data, safety events, plate recognition, weigh in motion	Event based, min two times a day	IEEE 802.11 /HyperLan /Fiber Optic	≤10ms

For each of them the main variables are highlighted, in addition to the communication protocol, the frequency and the delay for some communications. As seen in Table 1, most sensors use wireless technologies, with the exception of traffic flow sensors, which could also use wired infrastructures.

Delay requirements are in most cases from 100 to 500 ms, except for road works or traffic flow sensors that require real time information, subjected to selected QoS and nodes density. In the most highlighted cases event based communications are required.

V. CONCLUSIONS

In this paper the main IoT technologies for ITS in the main Smart Cities scenarios are evaluated. A main overview on communication protocols and innovative machine learning technologies that play an important role in this field is provided. Finally, additional analysis is conducted in practical scenarios.

Future tasks on this topic will be on the optimization of LoRaWAN localization and power management, integration of further smart cities technologies in different scenarios and an improved analysis on complexity of event based and periodic measurements for roads requirements.

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