Extendable and Interoperable IoT Architecture for Monitoring of Air Quality and its Dynamics

Chen-Wei Yang
Luleå University of Technology
Luleå, Sweden
chen-wei.yang@ltu.se

Aleksandra Dvoryanchikova
Naukatek AS
Trondheim, Norway
aleksandra.dv@naukatek.com

Vjatsheslav Kekshin, Juri Kubinets, Sergei Ponomar, Heiko Põdersalu
Tallinn University of Technology
Kohtla-Järve, Estonia
{vjatseslav.keksin, juri.kubinets, sergei.ponomar, heiko.podersalu}@taltech.ee

Andrei Lobov
Norwegian University of Science and Technology
Trondheim, Norway
andrei.lobov@ntnu.no

***Abstract*—Monitoring of air quality can bring awareness of what is happening in an urban area. If some pollutants exceed safe levels, one can try to identify the source of pollution to illuminate or mitigate the risk for humans and the environment. The UrbanBREATH looks at the air quality monitoring through instrumentation of ventilation systems in the urban area. It defines 3 levels of i) household or commercial/industrial site; ii) a district, where the household or the site is situated; iii) a municipality that is built of different districts. The UrbanBREATH solution addresses the need to trace-down pollution sources and the effects developed over the time. The solution is built on easy-to-integrate, extendable sensors base to potentially include different pollutants and to consider propagation distances for different pollutants dependent on meteorological conditions. (*Abstract*)**

Keywords—air quality, pollution, urban services, citizen science (*key words****)***

I. INTRODUCTION

Digitalization of urban services opens new possibilities to inhabitants. People can trace in real-time the spot prices for electricity, get notifications about collection of the specific garbage on their street at specific day, know how household water consumption changes over the time or plan better urban mobility thanks to real-time information about location of public transport. However, additional services also get conceptualized, such as a pollution-aware solution for pedestrians providing smart mobility service. This solution for pollution-aware pedestrian routing is discussed in [23]. It helps pedestrians to avoid polluted areas thanks to real-time pollution data analysis.

As technologies were developed, the concept of the Socio-Technical System (STS) was introduced by 1960 that highlighted "the reciprocal interrelationship between humans and machines and to foster the program of shaping both the technical and the social conditions of work" [24]. Interplay of technologies, tasks, structures and actors for development of Internet of Things (IoT) was studied in [25] through the socio-technical analysis and the STS. The study [25] analysed how to achieve a balance considering different stakeholders. This is important for this paper, as a solution developed requires integration of various technologies and people in the context of creating, delivering and using urban services of air quality monitoring and analysis.

A human-centred design relying on STS for IoT design is presented in [26] considering services of smart cities, smart energy and the smart grid, smart transportation, smart factory, smart health and food & water tracking and security. The study proposed to arrange the IoT system into five-layer structure to tackle different issues separately, essentially applying the separation of concerns design principle. The layers are sensing and control, networking, resource management, information processing and application layer. The smart city concept as a socio-technical system was presented in [27]. The study proves an approach on how the smart initiatives can be started and managed for a city considering 4 main pillars of i) technology, ii) task (functions), iii) structure (organization), and iv) people.

Considering many dimensions of socio-technical systems and relevant enabling technologies, the UrbanBREATH project is set to develop extendable and interoperable IoT solution for monitoring of air quality and for analysing air quality dynamics to mitigate pollution and health/well-being related risks. Different stakeholders should be integrated to such a system form household owners to municipal authorities. The focus in this paper is given to the IoT system as a first physical layer for interacting and precepting the environment.

The rest of the paper is organized as follows. Section 2 addresses state of the art including that of air quality metrics and enabling technology. Section 3 presents an architecture for the IoT-based extendable and interoperable system to monitor and analyse air quality. The solution is elaborated with different scenarios using UML sequence diagrams. Section 4 outlines the discussion about usability of the approach. Conclusions are drawn in section 5.

II. State-of-the-Art

A. Air Quality Metrics

To evaluate air quality and be able to monitor its dynamics or development through a distributed network of sensors, one should decide what to look for in the air. In [1], recommendations on classical air pollutants are given. The report opens with the statement that "clean air is fundamental to health" and it highlights six pollutants. These are particulate matter (PM2.5, PM10), ozone (O3), Nitrogen dioxide (NO2), Sulphur dioxide (SO2), and Carbon monoxide (CO). Each of the pollutants is studies based on its short-term and long-term effect including association between pollutants concentrations and mortality. The discrepancy between indoor air quality benchmarks is discussed in [3]. The study focuses on U.S. use cases, but in its state of the art also refers to European and Japanese standards. Four pollutants or contaminants levels are compared between the standards, these are CO2; Total Volatile Organic Compounds (TVOC), which represents combined concentration of multiple VOCs or carbon-based chemicals; PM2.5 and PM10. As can be seen from the paper [3], different standards include many different pollutants, as for example, benzene (C_6H_6), formaldehyde (CH20), toluene (C6H5CH3), which are examples of VOCs, or radon (Rn).

In general, each pollutant has its corresponding levels of concentration that become harmful for people. There are some sensor commercial solutions that have been implemented. Kunak AIR Pro [2] page lists "the widest range of pollutants" containing 23 pollutants in addition to temperature, humidity, atmospheric pressure and dew point measurements. However, the Kunak AIR Pro can only monitor "up to 5 pollutants and particles simultaneously".

There are different national, regional and industry specific standards for controlling air quality. In [4], evolution of air quality standards for thermal power plants in China is discussed. It shown that the standards are gradually improving leading to reduction of emissions over the time. The study [4] focuses on three pollutants, that is sulphur dioxide (SO2), soot (dust), i.e. PM2.5 (diameter of particles less than 2.5 micrometres) and Nitrogen oxides. Japanese perspective on environment quality standards (EQS) and its Basic Environment Law discussed in [5]. The EQS and the values were established for 17 chemical substances along with description on how these values were determined historically together with the procedures to set these values [5]. The study reports five classical (or traditional) air pollutants, which are sulphur dioxide (SO2), carbon monoxide (CO), suspended particulate matter (SPM), nitrogen dioxide (NO2), and photochemical oxidants (Ox) and 12 hazardous air pollutants. That can be seen as historic development of the EQS, where new pollutants were introduced over the time.

In the development of the air quality standards, various studies are preformed to show cause and effect relations between the pollutants and the negative impacts including death of humans. Importance of toxicology in additional to epidemiology studies is highlighted in [6]. The study [6] citing [7] shows a "pyramid summarizing the adverse effects of ambient O3". The effects of a pollutant can be at different levels, besides the most severe effect (death), people on a large scale (summed up for a population to millions of days per year) can be restricted in their activities.

The study [8] focuses on estimating the effect on air pollution made by the first change in gasoline standards is based on data collected from 1492 air quality monitoring stations providing hourly pollution data in years 2013-2015. It looks at composite measure of pollution, which includes PM10, PM2.5 and ozone (O3) as these "are particularly related to fuel composition and are among the most harmful to human health." [8] As conclusion, the study claims that "the adoption of higher gasoline standards significantly reduces local air pollutant concentrations, including those of PM and ozone" [8].

In their work [9] on an environmental air pollution monitoring system, the authors mention that there are identified 384 hazardous gases in the environment. However, the priority is given to six pollutants, which are CO, NO_2, ground level O_3, SO_2, Particulate Matter (PM), and lead as these are "the most dangerous and are known as 'the common air pollutants' or 'criteria air pollutants.'" So, an implementation is demonstrated for 4 first gases in the list, i.e. CO, NO_2, O_3, and SO_2.

Besides looking at specific gases, a "user" or "application" perspective can be adopted for specific cases. That is, tobacco and pollen. There was a big societal shift in recent decades on where people can smoke. Also, pollen cases widespread health issues related to pollen allergies. Thus, sensor solutions looked from some societal habits (e.g. smoking) and nature phenomena (e.g. pollination) can provide additional insight into how to define air quality.

A simple sensor solution for measuring tabaco smoke particles based on phototransistor and light emitting diode was demonstrated in [10]. As the sensor solutions become more affordable and easier to deploy, wearable sensors-based solution was developed in [11]. Thus, movable and mobile sensors solutions can be a worth-looking alternative to stationary, static deployments. Recent study [12] has shown that there were "no studies identified as eligible for evaluating the validity, reliability, or acceptability of pollen sensors ". A stationary solution for monitoring pollen described in [13] is said to show correlation with the symptom data obtained from people. A pollen sensor based on polarization optical sensor is discussed in [14]. A polarization factor for pollen is studied for improving detection. A link to [10] can be made here as the polarization is linked to the scattering effect of light. In the recent years, also low-cost affordable solutions, such as based on Raspberry Pi got developed [16].

Finally, different urban areas may also have different signatures or exposures to the pollutants [15]. Thus, the knowledge about the air quality monitoring system deployment area can be integrated for setup and analysis.

As this short state-of-the-art of air quality metrics has shown, there are different standards for measuring air quality. However, these converge and agree on most "standard" or classic pollutants. As was described by World Health Organization [1] and mentioned in [4], [6], [8], [9], [15], the UrbanBREATH project sets its focus in the beginning on the particulate matter ($PM_{2.5}$, PM_{10}), ozone (O_3), Nitrogen dioxide (NO_2), Sulphur dioxide (SO_2), and Carbon monoxide (CO). Under $PM_{2.5}$ and

PM_{10} one can also include user-centric stories such as tobacco and pollen exposure.

Overall, an approach for the Air Quality Metrics we suggest is to cover the most remarkable pollutants based on prioritization discussed in this section. In addition, to build an extendable knowledge base of pollutants that can be populated with the time with the descriptions of new pollutants and corresponding technical, also potentially evolving, solutions. It means that hardware solution proposed should have means to add new sensors for detecting new pollutants. Also, the software solution should support such expendability in a seamless way.

B. Enabling technologies

Recent studies have increasingly combined IoT technologies with **Machine Learning** (ML) techniques to enable real-time air quality monitoring, prediction, and decision support. These approaches have been applied across diverse deployment contexts and utilize a wide range of ML and Deep Learning (DL) models to address different air quality challenges. Mazinani et al. [15] evaluated several ML, DL, and quantized models for PM2.5 prediction using data from low-cost IoT sensors deployed at Brindisi Airport, Italy. Among the evaluated models, CNN-BiGRU achieved the best overall performance, providing the highest prediction accuracy while balancing computational complexity, memory usage, and execution time for edge deployment. Janardhan et al. [16] propose an IoT and ML-based air pollution monitoring system that combines real-time air quality sensing, health advisory generation, and pollution-aware route optimization. The system employs ESP32-based IoT nodes equipped with MQ-135 sensors to monitor pollutants and a Decision Tree Classifier is used to analyse pollution levels to generate personalized health recommendations and predictive advisories. Bogdanović et al. [17] investigated the application of ML and DL techniques for Air Quality Index (AQI) classification in large-scale IoT monitoring networks. The study addresses the challenges associated with deploying dense networks of low-cost, low-accuracy air quality sensors, whose measurement errors can significantly affect AQI estimation. The authors evaluated nine ML algorithms and three DL models for air quality classification using a dataset of 145,440 pollutant measurements collected from five countries. The results showed that DL models achieved the highest classification accuracy and were more robust to measurement errors than conventional AQI calculation methods, making them particularly suitable for large-scale IoT deployments based on low-cost sensors. Shaban et al. [18] proposed an IoT-based urban air pollution monitoring and forecasting system that utilizes low-cost wireless sensing motes equipped with gaseous and meteorological sensors. The collected data are transmitted to an intelligent sensing platform for processing and forecasting, where ML algorithms such as Support Vector Machines (SVM), Artificial Neural Network (ANN) and M5P model trees are used to predict O_3, NO_2, and SO_2 concentrations. The results showed that multivariate models improved forecasting accuracy and that M5P achieved the best overall performance.

The combined use of **IoT** and **Semantic Web** technologies is widespread and well-studied in air quality monitoring systems. IoT sensors provide continuous collection and transmission of observation data streams, while Semantic Web technologies make it possible to represent the obtained data in a machine-readable and contextualized form. In particular, semantic models allow not only the numerical value of a measurement to be described, but also its semantic context, including the type of pollutant, unit of measurement, location, observation time, the sensor used, the feature of interest, measurement conditions, and additional metadata.

One of the key foundations of such systems is the W3C/OGC Semantic Sensor Network ontology and its lightweight core SOSA, which provide a common model for describing sensors, observations, observed properties, features of interest, procedures, and measurement results [19], [20]. In the field of air quality monitoring, indicators such as PM2.5, PM10, NO_2, O_3, SO_2, CO, as well as temperature and humidity, are particularly important because they allow both the level of pollution and the conditions affecting the dispersion of pollutants to be assessed.

Domain-specific studies have applied semantic annotation directly to air-quality data streams. For example, IoTSAS proposed an approach for real-time semantic annotation and interpretation of IoT sensor stream data and evaluated it in air-quality monitoring and weather-alert scenarios [21]. A related study presented a real-time IoT-based air-quality monitoring system in which Sensor Observation Service data were enriched with semantic annotations, enabling individual measurements to be linked with their contextual information and improving the interpretability of sensor data streams [22].

Before more applied solutions appeared, the IoT–**blockchain** combination in air quality monitoring systems was used primarily as a layer of trust and data protection, rather than as a measurement mechanism. The literature proposes a split between a local lightweight blockchain and a public blockchain: the former is used for buffering and hashing records, while the latter is used for long-term data storage, reducing dependence on a central server and improving the traceability of measurements [28]. In more recent approaches, this scheme is supplemented with edge computing and smart contracts, allowing the system to move from simple data collection to real-time monitoring and automatic response to threshold exceedances [29]. Thus, blockchain is currently used mainly not for the sensing itself, but for the protection, verification, and distributed management of air quality data.

III. Approach

A. UrbanBREATH IoT architecture

The UrbanBREATH architecture adopts a layered approach to promote openness, interoperability, and extensibility across heterogeneous urban systems. The layered architecture provides a foundation for building an open and vendor-neutral ecosystem in which devices and services from different stakeholders can cooperate through standardized interfaces while remaining adaptable to future technological developments and evolving requirements, thereby supporting long-term interoperability and system evolvability. The architecture is built on the principle of separate of concerns, where physical devices, communication infrastructure, data and knowledge management services and

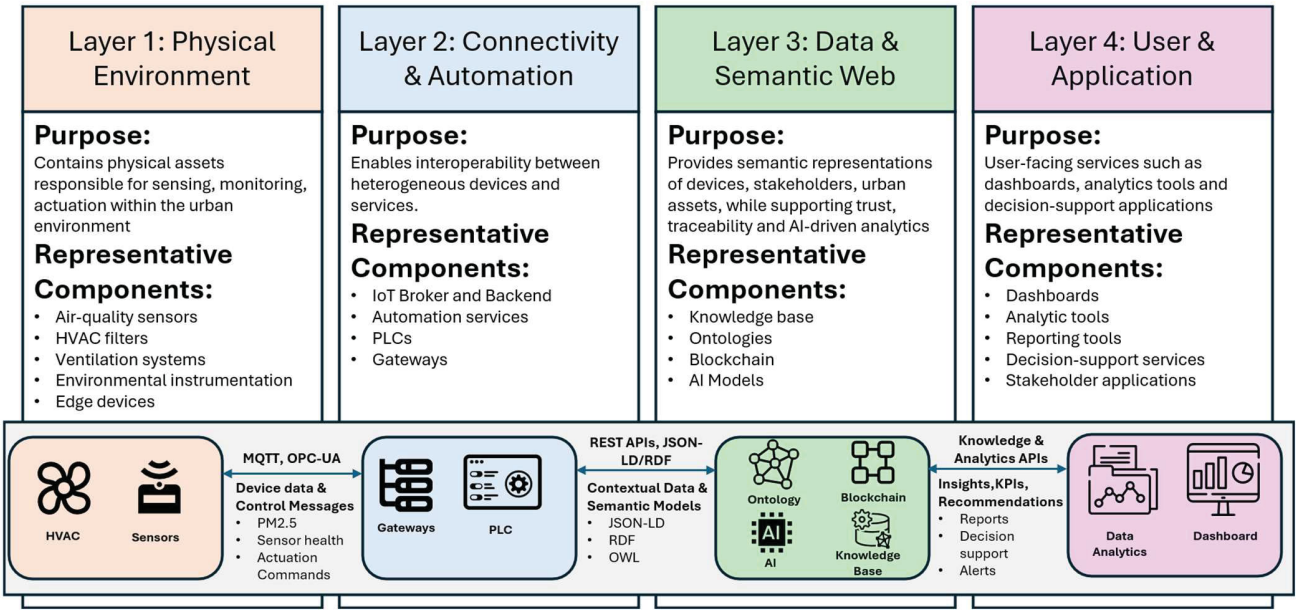


Fig. 1. The UrbanBREATH four-layer reference architecture

user-facing applications (pictured in Fig. 1) are intentionally organized into distinct layers. This architectural decoupling allows heterogeneous sensing, communication, analytics, and application technologies to be integrated through stable and standardized interfaces while enabling individual components to evolve independently. The layered design also promotes extensibility by allowing new devices, services, data models, analytics capabilities, and user applications to be added without requiring significant modifications to existing system components. Interoperability is maintained through well-defined communication interfaces, protocols, and shared information models. The breakdown of the layered architecture is as follows:

1) Layer 1: Physical Environment

The physical environment layer contains the primary physical devices that interact directly with the urban environment. Representative components at this layer include air-quality sensors, HVAC filters, ventilation systems and other environmental instrumentation devices. The primary role of Layer 1 is to collect measurement data from the urban environment and, where applicable, execute control actions on physical assets. Data generated at this layer are transported to higher layers through interoperable communication interfaces and standardized protocols.

2) Layer 2: Connectivity and Automation

The Connectivity & Automation layer enables interoperability between heterogeneous devices, systems, and services. Its primary function is to collect, transport, normalize, and route device data while supporting automation and control functions. Representative components at this layer include IoT brokers (message exchange and communication), gateways (integration of heterogeneous devices), backend services (data processing, orchestration, and service integration) and industrial automation platforms that communicate through standardized protocols such as Message Queuing Telemetry Transport (MQTT) and Open Platform Communications Unified Architecture (OPC UA). By abstracting device-specific details and communication mechanisms, Layer 2 provides a unified interface for integrating physical devices with higher-level services. This abstraction simplifies system integration and supports plug-and-play interoperability by enabling the discovery, registration, and integration of heterogeneous devices and services through standardized communication protocols and interfaces.

3) Layer 3: Data and Semantic Web

The Data and Semantic Web layer transforms device data into contextualized and actionable information. The two primary functions of layer 3 is traceability and trust management through blockchain-based mechanisms, and analytics and decision support through Artificial Intelligence (AI)-driven models. Semantic representations of devices, stakeholders, and urban assets are maintained using ontologies and knowledge bases, providing a common contextual framework for interoperability. AI models consume contextualized knowledge to generate insights and recommendations, while blockchain services ensure the provenance, integrity, and traceability of information exchanged within the UrbanBREATH ecosystem. Together, these capabilities make Layer 3 the knowledge-processing core of the UrbanBREATH IoT architecture.

4) Layer 4: User and Application

The User & Application layer provides user-facing services for different stakeholder groups, including residents, building operators, maintenance providers, municipalities, and researchers. Layer 4 delivers dashboards, analytics tools, reporting services, and decision-support applications that consume contextualized information generated by the lower layers. Rather than interacting directly with physical devices, applications access knowledge, insights, KPIs, and recommendations through well-defined service interfaces. This layer ultimately translates technical system information into

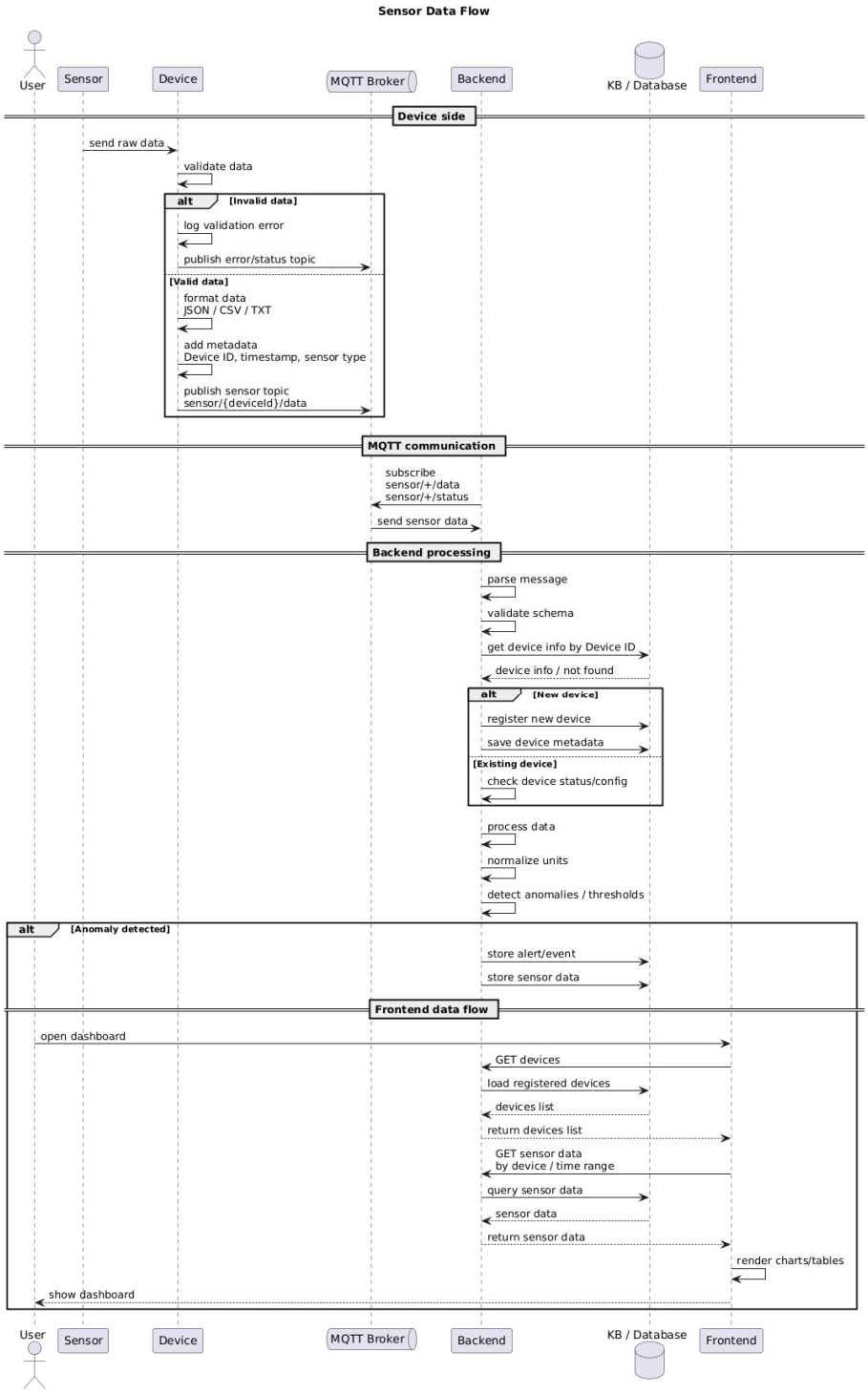


Fig. 2. Architecture interplay: Interacting with a device, MQTT communication, backend processing, and frontend data flow.

actionable knowledge that supports informed decision-making and operational optimization.

B. *Architecture Interplay*

After introducing the higher-level view on the architecture in the previous subsection, the Unified Modelling Language

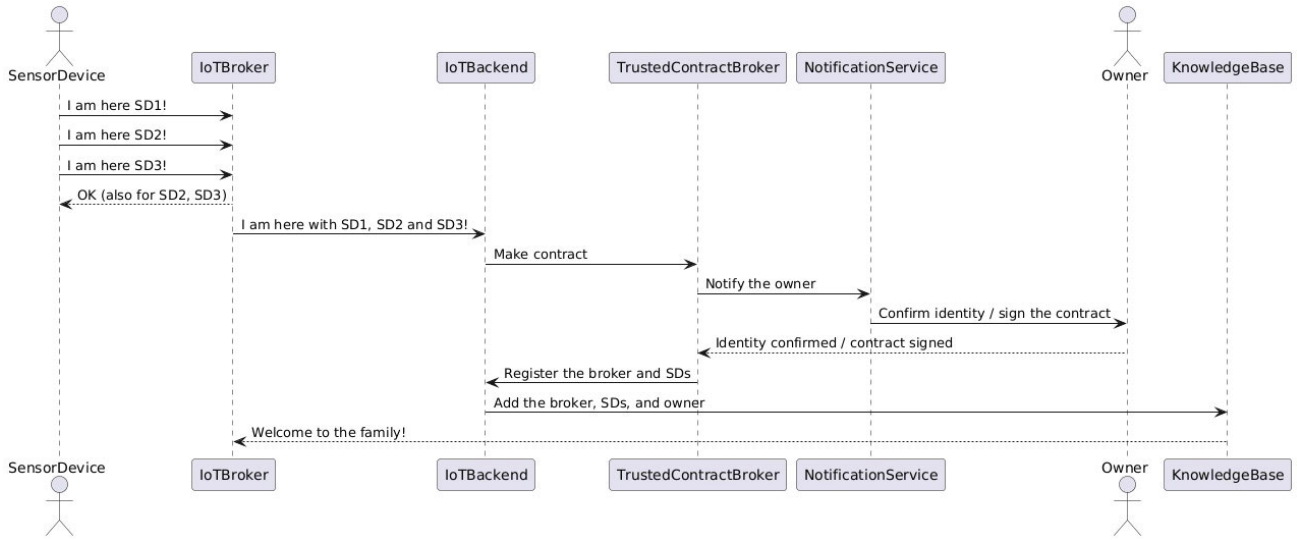


Fig. 3. Device onboarding scenario using blockchain TrustedContractBroker.

(UML) sequence diagram in Fig. 2 shows different scenarios of interacting with a device, MQTT communication, backend processing, and frontend data flow.

Starting with the sensors, these measure HVAC parameters and transmit the data to a local device, which performs analysis and validation. If the data is missing or incorrect, the device sends an error message to the central system. The use of edge computing enables data processing closer to the source, reducing network traffic and dependence on connection quality [30]. The valid data device formats it into a supported format such as JSON, CSV, or TXT. Then it adds metadata, including the device ID, timestamp, and sensor type. After that, the device publishes the message to an MQTT topic such as sensor/{deviceId}/data.

Before receiving data from a device, the MQTT broker must be pre-subscribed to the corresponding topic associated with that device. Information about all registered devices is stored in the blockchain, while measurement results are recorded as hash values. After the data is received via the MQTT broker, the backend component of the system verifies its authenticity. If the validation is successful, the data is transferred to the database for subsequent storage, and the corresponding hash, together with the date and time stamp, is recorded in the blockchain [31]. The backend component of the system is responsible for processing and structuring incoming data, transforming it into the required format, and storing it in a database. Semantic Web technologies are employed to organize and present information to end users, providing semantic data representation and facilitating efficient data interpretation [32].

Through the web interface, users can select the data of interest as well as the preferred method of visualization. The most common forms of presentation include tables and trend charts. The backend component handles user requests, enforces access control policies, and provides the requested data. Following successful authentication and authorization, the information is transmitted to the frontend, primarily in JSON format, where it is transformed into a clear and user-friendly representation.

Blockchain is considered as an enabling technology within the UrbanBREATH architecture for managing trusted information flows among stakeholders. It provides a verifiable and auditable mechanism for recording events, decisions and interactions that occur throughout the UrbanBREATH ecosystem. The use of blockchain technology contributes to traceability (i.e. tracking of data origins and information exchange), trust (i.e. providing verifiable records of data provenance, stakeholder identities and operational actions) and accountability (i.e. allowing authorized stakeholders to validate, inspect and verify activities such as device registration maintenance operations and information update).

Fig. 3 further details an example device onboarding workflow illustrating how blockchain can be used to establish trust relationships, verify stakeholder identities, and register new devices within the UrbanBREATH ecosystem. In this scenario, a newly deployed SensorDevice at layer 1 announces its presence to the IoTBroker at layer 2. The device information is received by the IoTBackend, which coordinates the registration process and interacts with the TrustedContractTracker, a blockchain-based trust management service at layer 3. The NotificationService contacts the Owner, who verifies ownership and confirms the registration request. Once the verification process is completed, the device and its associated metadata are registered and become accessible through the KnowledgeBase at layer 3. This onboarding process establishes a trusted and traceable record of device ownership and registration while demonstrating the interaction between the physical, connectivity, and semantic layers of the UrbanBREATH architecture.

IV. Discussion

The proposed UrbanBREATH four-layer reference architecture is discussed here in terms of its four enabling technologies, including the IoT, Blockchain, Semantic Web technologies, and ML. These form the foundation of the project's

overall architecture and implementation. The integration of these technologies aims at seamless data collection, data integration, and intelligent analysis from various ventilation systems and smart sensors designed to monitor and assess air quality. The system features a user-friendly interface and provides predictive knowledge of air quality across different locations, including houses, rooms, buildings, and urban outdoor environments. This enables efficient monitoring, data-driven decision-making, and proactive management of indoor and outdoor air quality.

Blockchain technology [33] has recently emerged as a transformative solution for enhancing the security of IoT networks [34]. Fig. 4 presents the architecture of an IoT system based on the MQTT protocol for monitoring and data exchange between industrial equipment, a cloud MQTT broker, and user applications. The central element of the system is the cloud-based MQTT Broker, through which data publishing and subscription are performed between different devices and applications. The left bottom corner demonstrates one of the use case ventilation equipment, reporting information on some of selected "classical" (as defined in section 2) pollutants. The sensor data is integrated with the ESP32 board and sent via the MQTT broker to the authorized subscribers or stakeholders.

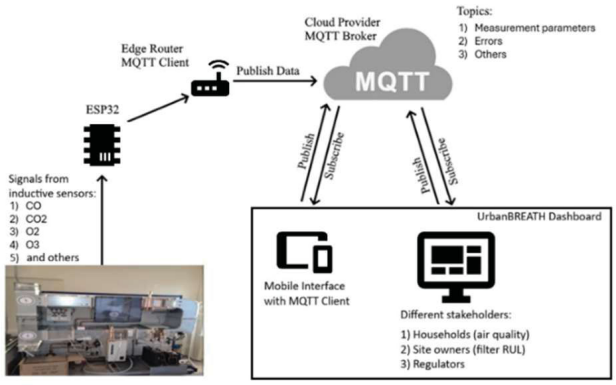


Fig. 4. Illustration of the UrbanBREATH architecture with MQTT-based solution and use case equipment (adapted from [35]).

The validity of data is based on blockchain. It has initially evolved to tackle issues related to security, integrity, energy efficiency, and latency of financial transactions [36]. Blockchain is the integration of the existing concepts of distributed ledger, cryptography, shared computing, peer-to-peer network architecture, and consensus mechanisms [37]. As a result, blockchain applicability depends on side technologies that enable it to interact with data in the ecosystem [38]. However, some limitations need to be considered, such as choosing the right blockchain, selecting the proper IoT technologies to partner with blockchain for information collection, and the choice of communication and security protocols [39].

Berners-Lee has defined the semantic web as a decentralized extension of the web of documents, where the information would have a meaning and would be machine readable [40]. A fundamental part of this web consists in the representation of the human knowledge through the creation of formalized semantic models, which can communicate each other, creating in this way an open, accessible, universal and connected bigger model [41], [42].

Semantic web is applicable for managing smart contracts, e.g. in context of air quality monitoring, mapping urban districts and capability of the device and its integrated sensors, i.e. revealing which data and on what pollutants can be collected at the site. The ML is a broad field of AI that enables computers to learn patterns from data using algorithms such as support vector machines, decision trees, random forests, or logistic regression [43]. Here, the ML serves for analysing air quality development dynamics to be presented to the relevant stakeholders via the UrbanBREATH Dashboard (right-bottom corner in Fig. 4).

V. Conclusions

The paper has presented an extendable, interoperable architecture in the context of air pollution monitoring (Fig. 1). The architecture is based on four enabling technologies that address different challenges such as a possibility of adding and validating a new device or a user, while growing a sensor network, proving access to authorized stakeholders. The information flows and stakeholders' authentication are to be managed with the blockchain, extendibility and interoperability is based on semantic web technologies, filed data collection and sensor base extension over the time are possible based on established IoT devices and protocols. Data analysis and support for decision-making is achieved by integrating selected ML methods.

Acknowledgment

The work is funded by the DUT Partnership, which is co-funded within the European Research and Innovation (R&I) Framework Programme, Horizon Europe.

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