Cloud Native approach to the implementation of an environmental monitoring system for Smart City based on IoT devices

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Abstract. In this paper, we present the architecture and implementation of the environmental monitoring system, which is one of the main elements of the Smart City system, deployed in a small town in Poland – Boguchwała, Podkarpacie. The system is based on the Internet of Things devices and Cloud Native techniques, which allow for measuring several environmental parameters like pollution, EMF pollution, and acoustic threats. In addition to these parameters, characteristic of environmental monitoring, the system has been enhanced with video monitoring techniques, such as evaluating the traffic intensity on the main roads and crowd detection. In particular, a front-end application was implemented to visualize the results on a city map. The system is deployed on Raspberry Pi and NVidia Jetson using Kubernetes as resources orchestrator. We managed to design, implement, and deploy a system that makes measurements and predicts the parameters indicated. The proposed solution has no significant impact on the energy consumption of the measuring stations while increasing the scalability and extensibility of the system.

Keywords: Smart City · Environmental monitoring · Cloud Native · Internet of Things

1 Introduction

One of the effects of systematic improvement in the quality of life is the alarming deterioration of the environment around us. In many places around the world, the concentration of air, water, or soil pollution threatens the health of the people who live and work there. Therefore, in the last decade, much attention has been devoted to counteracting the negative effects of urbanization and industrialization of further areas of our planet. One of the methods used for this purpose is monitoring the state of the environment, which allows us to track harmful phenomena occurring in our environment and take appropriate action at the right time. Monitoring can be carried out at three different levels: impact, regional, and background [1, 2].

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In this paper, we present the architecture and implementation of the environmental monitoring system, which is one of the main elements of the Smart City system, deployed in a small town in Poland – Boguchwała, Podkarpacie. In addition to the traditional parameters characteristic of environmental monitoring, the system has been enhanced with video monitoring techniques that allow for assessing the traffic intensity on the city's main roads and detecting clusters of people. For this purpose, machine learning methods were used, in particular object detection based on the YOLOv5 model with two setups: small and large. The system was built from IoT-based measurement stations, located in urban and suburban areas. The platforms used are Raspberry Pi for standard measurements and NVidia Jetson for video monitoring components. The system was implemented using the Kubernetes orchestrator, which enabled high scalability and expansion of the system with additional nodes. A front-end application was implemented to visualize the results on a city map.

2 Related works and contribution

In the available literature, a number of works of a similar nature to ours can be found. The essence of pollution measurement is the use of appropriate sensors. These devices can be an integral part of a larger platform or a separate software and hardware system. In their work [3], the authors describe the construction of an IoT class device that has the ability to measure pollutants from various ranges, together with the ability to send measurements to a remote server due to carefully planned communication. In addition to the set of many parameters and their presentation to interested parties, an important process nowadays is the prediction of pollutants, most often based on historical data. In [4], the authors present a model of a neural network based on a genetic algorithm, with which they predict the level of pollution depending on the time of day, with two defined time intervals: 1 hour and 24 hours. Thanks to a large set of historical data, it is possible to obtain a high accuracy, defined by a prediction error of less than 0.5%.

In the context of Smart City, in addition to monitoring the environment understood as natural phenomena and factors, it is important to monitor domains related to human activity, such as car traffic. In [5], the authors presented a model that limits the problems associated with both categories, i.e., reducing vehicle traffic and the resulting pollution. The use of historical pollution data to predict car traffic can also be found in [6]. The most important work related to the one described in this article is [7], because the authors set themselves the goal of collecting and presenting information on air pollution and street traffic. The system used the same classes of devices planned for our research, that is, Raspberry Pi and NVidia Jetson platforms.

In our work, in addition to the indicated information, forecasts of short- and long-term propagation of the indicated pollutants are made, the collection of which is much wider, because it goes beyond the aspect of air. The system also has the ability to measure electromagnetic radiation, called electromagnetic-

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magnetic (EMF) pollution. The big difference is also the implementation approach – in our work we focused on using Cloud Native techniques when designing the application, right from the very beginning. We use many methods of artificial intelligence to analyze the data collected by the system in order to reduce the volume of data sent to servers.

3 Methodology, system architecture and implementation

3.1 Data gathering

All data were collected in the city of Boguchwała and its vicinity. Measurement points were selected for this purpose, where the measuring stations described in the next part of the work were located. Their arrangement is shown in Fig. 1. Points 1-3 are not present because, in the current version of the system, they are located outside of the city and are used for other purposes.

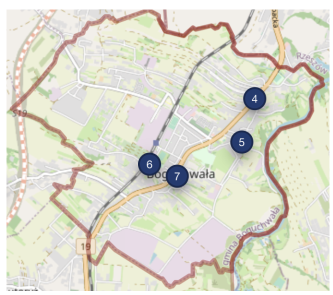

Fig. 1: Area visualization with measurement points

3.2 Data processing

Acoustic measurements The task solved in the system significantly exceeds the scope covered by modeling the propagation of acoustic waves. For the needs of the project, a new task was defined to determine acoustic disturbances along the actual route of movement of motor vehicles, which were initially decomposed into two subtasks. The first of the subtasks consists in building a spatio-temporal model of the displacement of disturbances along a given route and the known acoustic parameters of a set of their sources. The second subtask includes determining the distribution of sound pressure around the emitter based on a measuring device located at any point in the area analyzed. Contrary to the currently solved problems, it is not a set of stationary point perturbations that is considered, but a set of moving sources.

We assumed that communication streams as linear sources emit cylindrical sound waves, with the emission taking place into half-space. If these sources

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are located on an embankment or viaduct, radiation into space is assumed if the height of the embankment (viaduct) exceeds 3 meters. The distance R for which a cylindrical wave becomes spherical at the length of the sound source l is given by condition $R \geq l/\pi$. If the calculation point (the point at which the noise intensity will be determined) is the surface of a residential building, the equivalent sound pressure level L_{po} can be calculated using the expression:

$$L_{po} = L_{7.5} + 10\lg arctg\frac{l}{2R} - 10lg\left(1 - \alpha_{tlp}\right) - 10\lg\frac{R}{r_0}$$

where: L_{po} – sound intensity at the calculation point in dB; $L_{7.5}$ - sound pressure level at a distance of 7.5 meters from the road axis; $r_0 = 7.5m$; l – linear length of the sound source; α_{tlp} – surface attenuation coefficient.

Air pollution measurements Air pollution is one of the most problematic problems for Polish residents. For this reason, state and local authorities have built measurement networks that are independent of each other. The network built by the responsible state authorities is a high-budget, low-coverage metering network. The monitoring system provides real-time data and also offers modeling of air condition, which, however, is not made available en masse. On the other hand, systems made by local governments are based on low-budget measuring equipment and are limited to sharing the results at the measurement site, or possibly historical data. Spatial pollutant modeling services are not performed in them.

The maximum value c_m (mg/m^3) of the near-ground concentration of a harmful substance in the event of an unintentional release into the environment of a gas-air mixture from a single source with a circular outlet, obtained under unfavorable meteorological conditions at a distance of x_m (m) from the source, is calculated according to the expression:

$$c_m = A \cdot M\frac{F \cdot m \cdot n \cdot \eta}{H^2 \cdot \sqrt[3]{V_1 \cdot \Delta T}}$$

where: A – atmospheric stratification coefficient, for Podkarpacie $A = 180$; M [g/s] – mass of harmful substances introduced into the atmosphere per unit of time; F - dimensionless coefficient that describes the rate of deposition of harmful substances in the atmospheric air; H [m] – height of the pollution source above ground level; η - dimensionless coefficient taking into account the influence of the terrain, in the case of flat terrain or a slight slope not exceeding 50 m per 1 km, $\eta = 1$; ΔT [$°C$] – difference between the temperature of the gas-air mixture T_g and the temperature of ambient air T_p; m and n – coefficients taking into account the conditions of the gas-air mixture outflow from the outlet of the emission source; V_1 [m^3/s] - gas-air mixture outflow velocity.

Electromagnetic radiation measurements Information on environmental EMF pollution is currently one of the most sought-after data on the state of the

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environment. In the first place, EMF pollution comes from cell phone transmitters. Wireless networks at home can also be important. At present, there are no known serial field density sensors intended for use in environmental monitoring systems. The solution proposed in the system is to cooperate with the communication platform using Arduino. For spatiotemporal modeling of electromagnetic pollution, the system uses a methodology similar to that used in the case of air pollution. In this case, due to the rectilinear nature of electromagnetic wave propagation, the task of locating the source of the pollution is simplified.

Factors affecting the value of electromagnetic signal power density are most often: signal loss in free space, reflections and multipath effect, diffraction or shading effect, the need to penetrate rooms and cars by the signal, signal propagation over water and through vegetation, and various types of interference. Semi-empirical models are used to calculate the losses of radio signals during its propagation, the most famous of which are the Okamura-Hata, Walfisch-Ikegami, Ksya-Bertoni, Alsbrook and Parson models [8–10]. Statistical methods are also used to predict radio propagation losses.

Crowding and car traffic detection Gathering detection and traffic assessment are included in the same category of tasks. In both cases, the basis is a machine learning model that detects objects on frames sent by cameras. For this purpose, the YOLOv5 model was used. The model was trained to recognize two classes of objects: people and cars. It was taught using images of cars and people available on the Kaggle platform. Furthermore, the training and validation sets were enriched with 10% from the real work environment. Visualization of car traffic intensity is presented using sections of the road and a color gradient, indicating the intensity. An example is presented in Fig. 2. The figure also shows circles with a color gradient to indicate potential icing. The operation of this module is complex and is still in the testing phase, so it is not described in this paper.

Fig. 2: Visualization of traffic and crowding in the system

3.3 Cloud Native approach to the system

When designing the system, we had in mind that Smart City projects evolve and require the addition of new nodes; therefore, the system must be easy and highly

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scalable. For this reason, the system uses various Cloud Native techniques, in particular containerization and services as resources (e.g. queue, database server, FTP for updating microcontrollers). In addition, due to the nature of edge computing, we decided to use devices with high power consumption, such as Raspberry Pi for basic parameters and NVidia Jetson platforms for GPU calculations (YOLOv5 model). All edge devices do not have access to a permanent power source; they work with a battery charged with a solar panel.

The Raspberry Pi nodes are mainly used to collect information and send it to the aggregation node. In turn, Jetson nodes use the presence of CUDA cores to speed up machine learning calculations. We chose two models for testing:

– Nano, equipped with a 4-core ARM Cortex-A72 processor, 2GB of shared RAM, and 128 CUDA cores, consumes up to 7.7W of energy.
– AGX Orin, equipped with a 12-core ARM Cortex-A78AE processor, 64GB of shared RAM, 2048 CUDA cores, and 64 Tensor cores, consumes a maximum of 60W (also has 15W and 45W modes).

On the software side, for resource orchestration, we used the Kubernetes platform in the k3s version, dedicated to IoT class devices. The choice was dictated not only by Cloud Native issues, but also by the extensibility of the system. A broker based on Akri, which exposes sensors and cameras as resources in Kubernetes cluster, was launched on each of the nodes, detecting newly connected devices (including CSI and USB cameras). In order to increase the reliability of the system in the context of transferring information from nodes and to become independent of the frequency of their transfer, a Kafka queue was added to the system, to which measurement nodes send the results of measurements and/or analyzes.

4 Reliability and performance results

The last stage was to test the system in terms of performance, reliability, and accuracy of the models used. The verification procedure was divided into four stages: assessment of the possibility of adding new sensors and nodes to the cluster; checking the accuracy of the predictions of the models used; efficiency of the proposed software and hardware configuration in the form of detection times, transmission times, and numerical calculations and impact of applied solutions on energy consumption due to the power supply of the station battery.

As part of the first verification stage, efforts were made to add new sensors to measure the level of the river as the next stage of system development. For this purpose, a broker was written that reads and processes the values read from the sensor. The Akri broker automatically detected a device compatible with its implementation in the system, and Kubernetes launched the appropriate pods to support brokers. The next test involved adding a new node to the cluster. Thus, the first test was considered to have been met.

The second verification stage involves testing both specific measurement values and forecasts. The verification of the currently measured values was carried

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out manually with the use of specialized and calibrated instruments, i.e., a decibel meter, an air quality meter, and electromagnetic fields.

After the accuracy of the measurements made by the stations was confirmed, the forecasts of the mentioned parameters were verified. For this purpose, a simple program in Nodejs was prepared which was launched as a Job in Kubernetes. Its task was to regularly verify the measured values against the forecasts in order to continuously verify whether the accuracy did not change over time, which could suggest the omission of a factor in the models.

For numerically measured parameters, i.e. electromagnetic radiation, pollutants, and acoustics, the mean squared error (MSE) method was used. For machine learning models, standard tests were performed on a previously prepared test data set, composed of 80% (272 of 340 images) of data collected in Boguchwała. The accuracy obtained is presented in Table 1.

Table 1: Accuracy of the predictions

Parameter	Verification method	Value [%]
Acoustic threats	MSE	78
Air pollution	MSE	94
Electromagnetic radiation	MSE	89
Crowding and car traffic	Test dataset	92

Due to the nature of the parameters calculated from the images (crowding and car traffic), accuracy has a greater tolerance for errors because to mark their occurrence, a given threshold value must be exceeded. Incorrect detection in the number of two examples out of 10 does not change the classification to the indicated group. In the case of numerical parameters, it can be seen that the prediction accuracy obtained is high, although in the case of acoustic hazards, it is recommended to improve. During the implementation, it was noticed that the positioning of the microphones in each of the three dimensions has a great impact and the position opposite the measured space was not always the best position.

The third stage of verification assumed a list of performance and reliability parameters of the system. The use of the Kubernetes platform did not cause any performance loss – the CPU and memory consumption resulting from running k3s agents is less than 3% at idle. The most interesting comparison in the system was a comparison of YOLO network single inference times on Jetson Nano vs AGX Orin devices. In the case of Jetson nano, the average single frame analysis time was 147 ms for YOLOv5 small, while for Orin it was 43 ms for YOLOv5 large. It can be seen that at the moment the use of Jetson Nano is quite sufficient.

The last phase of verification required several tests at different times of the year, as it concerned the energy consumption of the solar-charged battery. In the case of Raspberry Pi and Jetson Nano devices, no impact was observed, both from the point of view of the calculations performed on them and the season. In

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the case of Jetson AGX Orin, the problem is to use its full power in the autumn and winter months, because the power from the solar panel is not enough to charge it. It can be used in 15W mode or by limiting the frame rate.

5 Summary and further works

As part of this work, a complex Smart City system was presented to monitor the environment based on IoT devices and cloud native techniques. The project used both analytical and non-deterministic models, based mainly on machine learning methods. We managed to design, implement, and implement a system that performs measurements and makes predictions of the indicated parameters. The introduced solutions in the field of Cloud Native not only enabled the scaling of the system but also not significant energy consumption, which would exclude this approach from application. The use of the Jetson platform speeds up frame processing, but in some cases it is not possible to use it (AGX Orin in winter). It is also planned to migrate the front-end part to the cloud and test the use of its other services.

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