Sustainable Computing: Informatics and Systems 31 (2021) 100588

Contents lists available at ScienceDirect

Sustainable Computing: Informatics and Systems

journal homepage: www.elsevier.com/locate/suscom

A crowdsensing platform for real-time monitoring and analysis of noise pollution in smart cities

Ivan Jezdović [a], Snežana Popović [b], Miloš Radenković [b], Aleksandra Labus [a], Zorica Bogdanović [a,*]

[a] Faculty of Organizational Sciences, University of Belgrade, Serbia
[b] School of Computing, Union University, Serbia

ARTICLE INFO

Keywords:
Smart cities
Noise pollution
Mobile crowdsensing
Big data

ABSTRACT

This paper presents a crowdsensing platform for real-time monitoring and analysis of noise pollution in smart cities. The aim is to develop a comprehensive methodology and scalable infrastructure for measuring noise using mobile crowdsensing, storing and analysis of gathered data. The developed system consists of: 1) a mobile application for participatory and opportunistic crowdsensing of noise data from different microlocations, pre-processing of collected data, and sending data to the cloud, 2) a big data infrastructure for storing data and real-time big data analysis, and 3) a web application for decision support. Further, we have created a methodology that lets us select priority microlocations not typically covered by stationary measuring. The system has been evaluated experimentally; more than 4000 measurements were collected at five microlocations in the city of Belgrade, Serbia. Data was analysed in order to find the patterns that could serve for decision support to different stakeholders.

1. Introduction

Noise can be classified as any loud, unexpected, unwanted or unpleasant sound. It can also be defined as a sound in the immediate environment, with detrimental effects on human hearing, health and quality of life [1,2]. Negative effects that noise can have on human beings can be classified into three groups: emotional, physiological and psychological (such as anxiety, sleep disturbance, or hearing impairment) [3]. Additionally, exposure to environmental noise can cause sleep disorders, high blood pressure and cardiovascular problems [4]. For these reasons it is necessary to pursue noise reductions in areas where it is significantly above the defined limits.

All cities generate noise, as it is a product of their regular everyday function, with traffic systems being the major contributor [5–7]. These urban environments often have regulations regarding noise as well as rules regarding their measuring. The measuring of this noise is conducted by authorized, professional organizations in accordance with legally defined rules [8]. Measurement locations, as well as rules of measuring, are defined by the local authorities, with respect to international regulative and standards [9]. Additionally, these laws and regulations often designate local government units with defining acoustic zones in their jurisdiction and the maximal values for noise indicators in these zones.

Acoustic zones are made in settlements, zones along highways, main and regional roads or in busy city streets where transit, freight or city traffic take place. These zones are usually broad in scope and can serve to give a rough idea of the local noise levels, but a problem arises if it is necessary to know the noise level at a microlocation. Due to the small size of microlocations, it is rare for them to be incorporated in systems for noise measurement. A possible solution to measuring noise at these locations is crowdsensing [10–13], a method that promotes the local population into engaging in noise measurement activities using their mobile devices.

The main goal of this research is the development of a mobile crowdsensing system for monitoring noise pollution in smart cities. Novelty of the work is reflected in the development of methodology with appropriate system implementation should enable collecting, storing and real-time visualization of noise pollution data. The data gathered in this way is showcased through advanced analysis of each measuring location, and its assorted noise indicators. These advanced analytics will be available in real-time, to both the citizens and government bodies, for any decision making regarding noise pollution management in smart

* Corresponding author at: Faculty of Organizational Sciences, University of Belgrade, Jove Ilića 154, 11000 Belgrade, Serbia.
E-mail address: zorica@elab.rs (Z. Bogdanović).

https://doi.org/10.1016/j.suscom.2021.100588
Received 20 February 2021; Received in revised form 15 June 2021; Accepted 6 July 2021
Available online 8 July 2021
2210-5379/

cities. The implementation and evaluation of the developed system were done in the city of Belgrade, the capital of Serbia.

The rest of the paper is organized as follows. Section 2 presents noise measuring methodology, existing solutions for noise crowdsensing and regulations related to measuring noise pollution. In Section 3, we present a mobile crowdsensing system for monitoring noise pollution developed for the purpose of this research. Section 4 describes the methodology used to discover critical locations and daily periods of extreme noise, while Section 5 gives the analyses of the results obtained in more than 4000 measurements on selected locations in Belgrade. Section 6 presents conclusions made during the course of the research.

2. Theoretical background

2.1. Noise measuring methodology

Noise indicators are used to determine the noise level in an environment [14,15]. In general, noise indicators are descriptors that express limit values of noise in decibels [16]. The value of environmental noise indicator is determined through the implementation of a measurement and estimation method, set by regulations or standards.

Before starting the noise measurement process, it is necessary to: define the objective of noise measurement, align the objective and implementation of noise measurement with existing regulations, define noise sources and time schedules of measurements [17].

Noise indicators developed for a specific context, such as a transport mode, although precise, can be hard to calculate, especially in complex environments that contain multiple noise sources. Therefore, both scientific and professional communities frequently use general environmental noise indicators, which are straightforward to calculate and understand [18]. The most popular general environmental noise indicator is $L_{den,}$ which weights the noise differently according to day(L_{day}), evening($L_{evening}$), and night(L_{night}) periods, allows the comparison among different infrastructures and can easily be represented through noise maps [18]. Noise measurement is carried out 24 h during a calendar day, which is divided into three reference time intervals:

- The day lasts 12 h (in period 6−18 h),
- The evening lasts 4 h (in period 18−22 h),
- The night lasts 8 h (in period 22−6 h).

Noise level L_{den} for the day-evening-night scheme is expressed in decibels is calculated with the following equation [19]:

$$L_{day} = 10\log\frac{1}{24}\left(12\cdot10^{0.1\cdot L_{day}} + 4\cdot10^{0.1\cdot\left(L_{evening}+5\right)} + 8\cdot10^{0.1\cdot\left(L_{night}+10\right)}\right)$$

where L_{day}, $L_{evening}$, and L_{night} are A-weighted long-term average sound levels, determined for all daily, evening and night periods over one year, respectively. A-weighting is the standard frequency-weighting filter for instrument-measured sound levels commonly used in many national and international standards [20]. It covers audio range 20−20 kHz and correlates with the loudness perceived by human ear. The measurements are expressed in dB(A) units.

Besides calculating noise indicators, noise characteristics can be studied by analyzing its frequency spectra. The Fast Fourier Transform (FFT) has been proven to be a powerful tool for analyzing noise characteristics [21]. One of the benefits of transforming the signal from time domain to frequency domain is that the volume of data is reduced, and consequently data can be transferred through a communication medium faster; however, due to intensive computational requirements, spectral analysis requires processor time and consumes high power [22].

2.2. Analysis of existing traffic noise measurement systems based on crowdsensing

Today, traffic noise data is usually collected by intelligent devices. In addition to simple measurements these devices can provide additional data and metadata; for this reason, a system for storing and analyzing this large amount of data is necessary. Recent advancements in IT, in particular big data technologies, have made it possible to efficiently store large amounts of data and offer advanced analytics in real-time. With the ubiquitousness of mobile devices, more convenient techniques for collecting noise data have emerged. Crowdsensing enables the gathering of environmental information through embedded sensors or other intelligent devices and transmission of captured data to interested parties [23–26].

Traditional urban noise measurement techniques are expensive and usually applied in the official noise measuring done by professional agencies [27]. In contrast to these techniques are studies that seek to explore the potential of mobile crowdsensing for measurement and analysis of traffic [27–30]. Most of these studies rely on mobile applications, such as EarPhone, NoiseSpy, NoiseTube, NoiseBattle and NoiseMap. Some of these applications are commercially developed applications available at app-stores for Android or iOS devices, while others have been developed for research purposes.

In the study [27] authors described the development of an EarPhone noise mapping system based on crowdsensing. EarPhone system consists of mobile applications and a central server. This system includes software for signal processing and noise measurement by mobile phone, as well as software for signal reconstruction on the central server. System testing involved measuring the noise levels at one of Brisbane's main roads during its reconstruction. The measuring was done for one week, in periods 8−9 h and 14−15 h. Eight measurements were made each hour, and in each hour participants walked for five minutes and collected the data. The authors of the study expect that their system will significantly reduce operation costs compared to using traditional noise recording and mapping systems.

NoiseSpy noise measurement system enables user collection and visualization of real-time noise levels while exploring different parts of the city [28]. This noise level measuring system uses a microphone on the mobile phone and a GPS receiver to determine the exact location of the measurement. System testing involved the use of courier bikes. During their routes, the system measures noise level and links it to the corresponding GPS data [28]. A similar concept for measuring noise was presented in the study [29] by testing the NoiseTube mobile crowdsensing application. Unlike others, the NoiseTube application offers the ability to attach tags to individual recordings, sharing data directly from the application and is available on different mobile platforms such as Android and iOS [31]. In addition to the mobile application, NoiseTube also includes a web platform that allows users to research, visualize, analyze and search data. NoiseTube is the application that corrects location in aim to partially reduce positioning errors [32].

The authors in the study [33] found an innovative way to animate citizens while collecting and sharing noise data. Using the NoiseDroid project open-source noise measurement system, that requires users to move around the city and perform noise measurements. The city is divided into blocks, which the user "wins" by trying to make more noise measurements than the other participants. Besides the number of measurements, the algorithm also takes into account the quality of the measured noise.

Researchers from the Technical University of Darmstadt have developed the NoiseMap application, which collects noise level data and sends it to the da_sense web platform [30]. The platform allows users to view collected noise data, generate graphs and noise maps. In a survey conducted in 2012, the researchers created a noise map for the city of Frankfurt, taking into account only the roads where more than 6 million vehicles pass annually. Unlike other projects, data is available using a public web service or JavaScript API.

Based on the literature analysis, it can be concluded that most of noise measurement systems utilizing crowdsensing in smart cities use: 1) mobile applications that use microphones to collect noise level data and a GPS receiver for the location of measurement; 2) web platforms for visualizing collected noise and location data. In the analyzed studies there are no plans for long term storing and management of large amounts of measured data or the capability of making complex analysis in real-time. The advantages of the developed system presented in this paper over the analyzed systems are 1) The developed system is devoted to storing data in a non-relational database, with straightforward deployment in the cloud; 2) data is collected for analysis of noise frequency spectra, which allows for a more sophisticated analysis of noise; 3) data analysis based on large amounts of measured noise data is available in real-time.

2.3. Accuracy and precision of noise measurements

Accuracy of devices for measuring noise, in terms of closeness of the measurements to a real physical values, has been considerd in the literature from multiple points of view. In the context of crowdsensing, the accuracy of using mobile phones for measuring noise is of special interest. Comparisons of mobile phones to calibrated sound level meters (SLM) have shown a generally acceptable level of accuracy, leading to conclusion that crowdsensing is an acceptable method for measuring traffic noise [34]. In general, the accuracy of the noise level measured by a mobile phone depends on the characteristics of the mobile operating system, manufacturer, model and physical condition of the mobile device [35,36]. In addition, the accuracy depends on the charactersitics of the microphone of the mobile phone. Results show that the linear range of a typical mobile phone microphone is 50–90 dB(A), which corresponeds to typical noise levels in urban environments [36].

The accuracy of the measurement can be imporved by the callibration of the mobile device. Callibration is usually done with SLMs. Due to the mentioned differences in individual mobile devices [35], it is not possible to uniformly callibrate the mobile phones of participants in crowdsensing; other approaches need to be applied [10,35,37]. The analysis of literature has not pointed out any solutions for uniform and generally applicable callibration, not even for the identical models of mobile phones [38]. One possible solution would require manufacturers to publish the technical instructions for callibration of their devices in accordance with the standards [39].

Besides accuracy, the quality of measurement depends on the precision, i.e. on the closeness of the measurements to one other. Precision depends on the configuration of the location, position of the mobile device in regards to the physical obstacles, orientiation of the mobile device, exposure of the microphone in regards to the noise source, etc. [36]. Additionally, the precision depends on the movements of the participant [40]. When there are many participants in the crowdsensing experiment, the precision can be improved by following strict measurement protocols [39].

In the context of data collection through mobile crowdsensing, it should be pointed out that the lower accuracy and precision of single devices can be effectively compensated through a high number of measurements using a high number of devices [41]. Higher reliability of summarized measurement results is achieved by combining data measured by numerous devices and applying different statistical methods and techniques for data cleaning, exploration and analysis [42].

2.4. Regulations for measuring traffic noise

The EU is considered to be the leader in the field of noise measurement [43]. Member States have been mapping noise for many years, due to the provisions in the EU Directive 2002-49-EC [44]. The directive has encouraged advances in noise measurement methods and the creation of noise maps for many major cities [45]. Regarding the noise pollution, the EU has different laws for road, rail and air traffic, as well as for the industrial noise sources. Within urban areas, only major roads, major railways and major airports are considered. Unlike in Europe, where noise mapping is mandatory, the United States and Japan have laws that date back to the 1970s, but noise mapping is optional. In developing countries there is a general lack of legislation for measurement, evaluation and control of noise levels [46].

Limit values for noise pollution in the Republic of Serbia are defined in the Regulation on Noise Indicators, limit values, noise indicators assessment methods, annoyance and harmful effects of environmental noise. Table 1 shows the limit values for outdoor noise indicators, distributed across different zones [17].

3. A mobile crowdsensing system for monitoring noise pollution in smart cities

In this research a mobile crowdsensing system for monitoring noise pollution in smart cities was developed. It consists of the following elements (Fig. 1): 1) crowdsensing mobile application, 2) cloud and big data infrastructures, 3) web application for monitoring noise pollution and data analysis, 4) a set of REST web services for communication between components.

The developed crowdsensing mobile application has the following functionalities (Fig. 2) [47]:

- recording noise using microphones from mobile devices,
- recording the location of detected noise in the city using a GPS device,
- performing spectral analysis over the audio data, and storing transformed data and location data in the cloud database,
- displaying the noise level spectrum for the performed measurement.

Performing spectral analysis consumes hardware resources, but it can be easily done on most of the smart phones. This leads to significant lowering the volume of data transmitted through the network, thus enabling quicker storing and analysis of measurements. Additionally, it contributes to the system scalability and leads to more efficient resource utilization [48].

The system supports three scenarios regarding the calibration of mobile devices:

1 Full calibration. In this scenario, the mobile phone is calibrated in the laboratory, using the certified sound calibrators. This approach gives the highest accuracy of measurements, but is hard to implement in the crowdsensing experiments, since it would require a high number of participants to bring their phones to the laboratory. This approach also assumes other calibration techniques that require the usage of

Table 1
The limit values for outdoor noise indicators in Republic of Serbia.

Zone	Use of space	Noise level in dB	
		day and evening	night
1.	Rest and recreation areas, hospital zones and spas, cultural and historical sites, large parks	50	40
2.	Tourist areas, camps and school zones	50	45
3.	Purely residential areas	55	45
4.	Business-residential areas, commercial-residential areas and playgrounds	60	50
5.	City centre, trade, administrative zone with flats, zone along highways, main and city roads	65	55
6.	Industrial, storage and service areas and transport terminals excluding residential buildings	The noise level mustn't exceed the limit value of the adjacent zones	

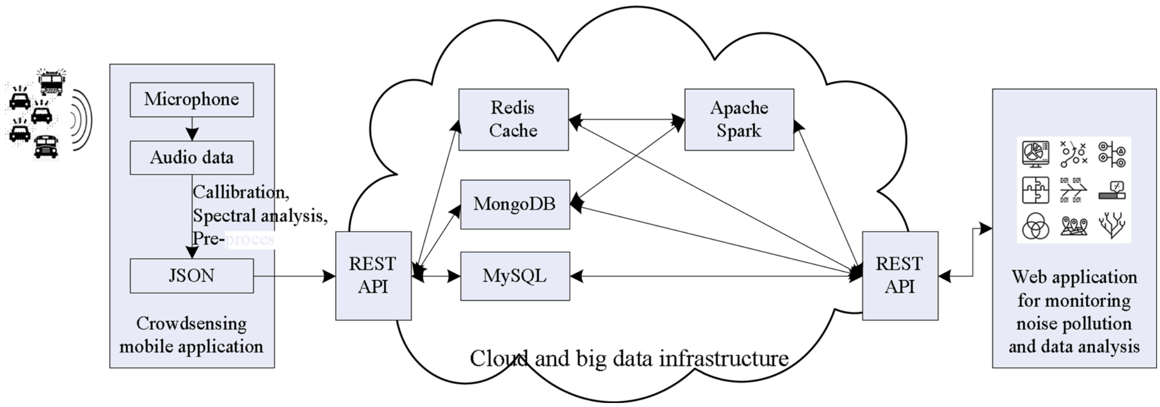

Fig. 1. A mobile crowdsensing system for monitoring noise pollution in smart cities.

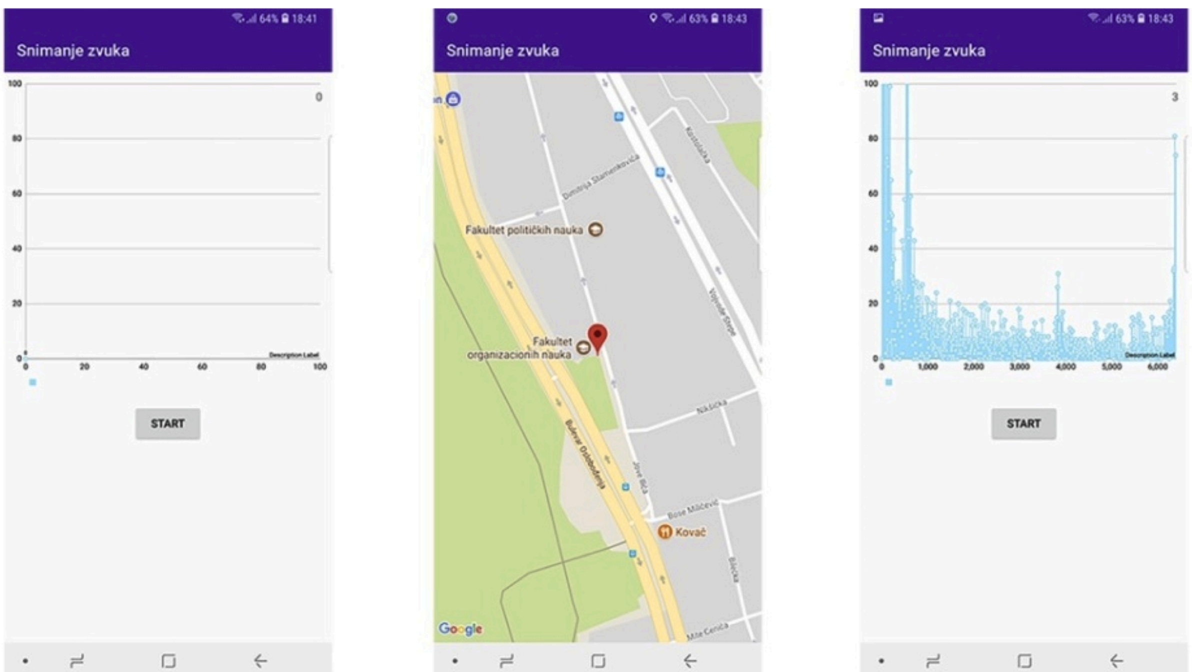

Fig. 2. Crowdsensing mobile application.

calibrated microphones, other mobile phones or similar devices for calibration [49].

2 Calibration based on the model of the mobile phone. The developed mobile application can perform a general calibration of the mobile device based on the specific model of the mobile phone. The calibration is done by using the calibration data of other devices of the same model, if available in the database. The calibration is done remotely, upon user's request. This approach does not provide the highest level of accuracy, but certainly contributes to the higher accuracy of measurements. The approach can be applied only to the common models of mobile phones, largely used in the participating population. Additionally, this approach can be improved in cases where phone manufacturers provide instructions for device calibration.

3 No calibration. This approach is the most common in typical crowdsensing contexts. It provides the lowest accuracy of individual measurements, but an acceptable level of accuracy of summarized results based on the statistical methods and strong data post-treatment [50].

The main component of the system relies on the cloud and big data infrastructure. The server hosting the RESTful API is located within the cloud infrastructure. The RESTful API was created using the Flight framework [51]. The use of this RESTful API, allows us to make web services which can offer a scalable and straightforward way of accessing various data and actions provided by the underlying systems hosted on the same cloud infrastructure.

Due to the limitations of NoSQL databases when it comes to schema design, a conventional relational database was chosen for the purpose of designing a model for calibration of mobile devices. A strict and structured database schema would remove any potential problems that could arise from changes in the data, data format, and any potential data constraints. The system calibration schema is shown in Fig. 3 (For the simplicity, only the most important attributes are shown).

By using a relational database to store user data and other data related to the user interaction in the web app, we have drawn a clear boundary between the storage of measurement data which is done by MongoDB and Redis, and mobile phone configuration and web app management which is done strictly by MySQL. This hybrid approach is expected to enable the implementation of various services that require

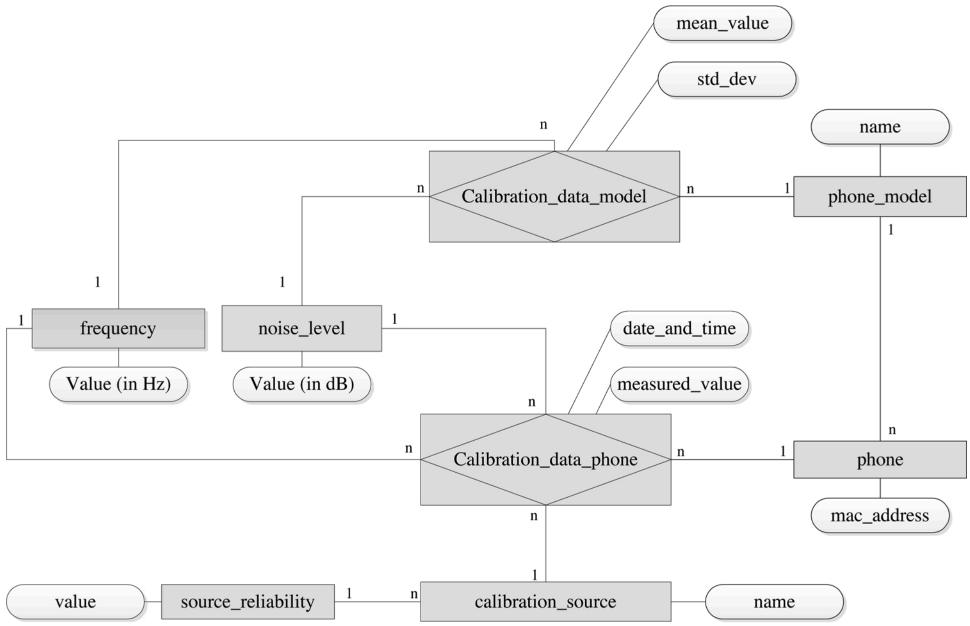

Fig. 3. Data model for device calibration.

querying data simultaneously from relational and non-relational systems and advanced data analysis techniques for developing prediction models.

Due to the large amounts of data collected through the crowdsensing mobile application, the system requires a big data infrastructure capable of storing large volumes of data in an efficient manner. MongoDB was chosen for this task due to its performance and storage capabilities. The data stored in MongoDB is primarily related to user measurements, and its primary task is to serve as a datasource for Spark analytics. Currently, MongoDB holds the following data: location data, maximum and average volume in dB(A), a complete spectral analysis result, i.e. a range of frequencies and their amplitudes.

Redis is used as an in-memory data store for acceleration, caching and session management. Redis uses both MySQL data and MongoDB data for caching purposes, in order to speed up frequent queries, and web application based tasks. By coupling MongoDB and Redis with big data analytics in Apache Spark we can provide noise analysis in real-time and deliver the results to a user-friendly web application.

Advanced analytics can be done by building and running models in Apache Spark. Possible scenarios include: detecting specific noise patterns, detecting deviations from typical noise profiles, predicting noise levels at specific locations, detecting the structure of the traffic by noise patterns, etc. While the current volume of data is relatively low compared to most Apache Spark workloads, the choice of Apache Spark as a platform was made with scalability of the system in mind. Future works and extensions of the system will bring increased volumes of data,

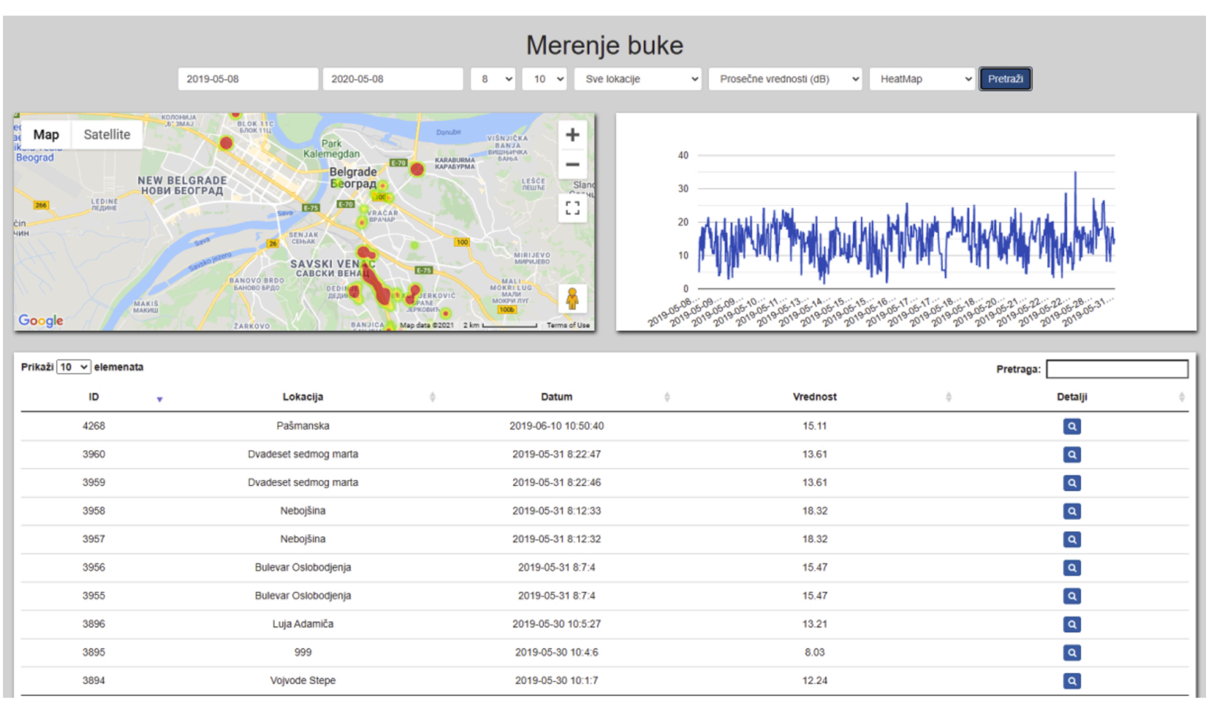

Fig. 4. Web application.

and the real-time analytics are expected to be relevant for noise pollution decision making related to control of IoT systems.

The web application allows users to fully view, search and sort data about measured noise values (Fig. 4). Noise values at different locations in the city can be displayed in tables, maps and charts. The map contains markers of the recording locations; each marker contains metadata for individual measurement, such as location name, geolocation, recording time, and description. The web application allows downloading complete spectra of the gathered data.

Some of the typical queries and use cases for the web application are:

1 Predefined reports, such as heat map for the previous day, latest measurements, etc.
2 Interactive search of the noise intensity by different parameters, such as by day, by month, by microlocation, by noise level, by frequency interval, or by any combination of these parameters.
3 Advanced analytics can be presented by building and running models in Apache Spark
4 Developing custom applications based on the provided API.

4. Methodology and experimental settings

Planning noise measurement requires several decisions: the choice of sensing methods, participants, devices, locations, and measurement periods. In relation to how participants are engaged, the most commonly used sensing methods are opportunistic and participatory. Opportunistic sensing is automatic data collection, where data collection does not occur in predetermined locations and time but rather during free and random movement of participants. Contrary to the opportunistic method is the participatory sensing method where the place and time of the measurement is predefined by the research organizer [52]. For this study, we chose the participatory sensing method because the number of participants and time of measurement were limited [53–55]. However, the users' devices were not calibrated, in order to get insights into the quality if data that would be gathered in typical crowdsourcing scenarios.

The participatory sensing method requires selection of the representative locations for measuring. A possible way to identify the required number of critical, representative locations of different types is based on similar patterns of traffic flow [56]. After selecting the locations, participants are expected to visit the monitoring locations at some point, activate crowdsensing mobile application and, while moving randomly, spend 10 min at the assigned locations. Noise measurements at assigned locations are performed simultaneously by groups of two participants, using their mobile devices with installed crowdsensing mobile application, recording 10 audio clips, for one minute each.

To implement the planned scenario, we propose a methodology that can support:

- Location selection based on criticality assessment. The coefficient of criticality of candidate locations are determined on the basis of existing experience, knowledge and similar patterns of traffic flow. Some of the conditions are: traffic configurations (roundabout, street, crossroads, traffic lights, pedestrian crossings, speed); legal categories and characteristics of traffic participants (passenger cars, trucks, buses, rail vehicles). Depending on the observed location, the set of listed parameters that affect the noise level may be expanded with additional relevant parameters.
- Recommendation of days and intervals for noise measurements.
- Inclusion of additional factors that influence noise level. The noise level can also be influenced by: meteorological conditions (rain, snow, wind); type and quality of roadway; natural and artificial sound barriers etc.
- Using measurement results, drawing conclusions and recommendations. The results of data processing are presented in the form of conclusions and recommendations and they are available for future research and application.

4.1. Location selection

During the course of planning the experiment, following steps were taken: location description, determination of days, intervals and lengths of measurements and calculations of critical noise pollution coefficients.

Location selection is based on an assessment of the criticality coefficients of the location. The cumulative noise coefficient R, at a specific location, is estimated based on the influence of weighting factors. Estimation includes several successive steps:

1 **Identifying the permitted vehicle categories on the location** The set of permitted categories of vehicle in the observed location is a subset of the prescribed vehicle categories by the statutory and standards.

$$\mathbf{S} = \mathbf{S}\{\mathbf{i} \mid \mathbf{i} \leq \mathbf{n}\} \subseteqq \mathbf{V}\{\mathbf{n} \mid \mathbf{n} \in \mathbf{N}\} \tag{1}$$

where: **S** - a subset of legal categories of vehicles allowed to pass through an observed location; **V** - a set of all legal vehicle categories; **n** - total number of legal vehicle categories.

2 **Calculation of the relative noise values of the vehicle categories on the location** Based on the maximum, legal noise level of each vehicle category **Lmax(i)**, from the set of **S**, calculate the relative value **λ(i)** with respect to the vehicle category, which, by standards and regulations, has the maximum noise level **Lmax**, and belongs to S:

$$\lambda(\mathbf{i}) = \mathbf{Lmax(i)/Lmax} \tag{2}$$

where: **λ(i)** - the relative noise value of the observed vehicle category; **Lmax(i)** - maximum permissible noise level of the vehicle category **i**; **Lmax** - maximum permissible noise level, comparing the **Lmax(i)** categories of vehicles that belong to **S**. Values of **λ(i)** are location independent. The assumption is that technically correct vehicles participate in traffic and that they comply with the established traffic regime and current traffic regulations.

3 **Estimation of the time participation of individual vehicle categories in a location** Measure or estimate the relative time participation of individual vehicle categories **τ (i)** in the observed measurement period **T** at the observed location is:

$$\tau(\mathbf{i}) = \mathbf{t(i)/T} \tag{3}$$

where: **τ(i)** - relative time participation of individual vehicle categories in relation to the continuous measurement period; **t(i)** - total time of participation of a certain category of traffic in the observed, continuous period; **T** - continuous measurement time interval.

The relative temporal involvement of the vehicle can be measured at the observed location. In case when research resources are limited and measurements cannot be made, indirect information can be used. For example: frequency of city traffic at a location based on timetables of public transportation, traffic count results, etc.

5. Incorporation of location correction factors

The noise level also depends on the type and configuration of the location, meteorological conditions, traffic regulation at the specific location, etc. The correction factor is calculated as follows:

$$\mathrm{C} = \sum\nolimits_{j=1}^{J} \mathbf{c}(\mathbf{j}) \tag{4}$$

where: **C** - cumulative location correction factor; **c(j)** – additional impact on noise level (sound barriers, type of roadway, periodic noise source: stadium, ambulance, fire department, police). If: **c(j)<1**, the factor reduces the noise level; **c(j) = 1**, the noise level is not affected by the factor and **c(j)>1,** the factor increases the noise level. The cumulative correction factor is not easy to evaluate without concrete measurements. It requires elaboration and detailed studies, so they are not the subject of this paper. In case they are not calculated, adopted value is: **C = 1**.

6. Cumulative noise coefficients in a location as a product of individual factors

The cumulative noise coefficient **R**, at a specific location, is estimated based on the influence of the calculated weighting factors **λ(i), τ(i)** and **C**:

$$\mathbf{R} = [\ \textstyle\sum_{i=1}^{n} \boldsymbol{\lambda}(\mathbf{i}) * \boldsymbol{\tau}(\mathbf{i})] * \mathbf{C} \tag{5}$$

where: **λ(i)** - the relative noise value for the vehicle category **i**; **τ(i)** - the relative temporal participation of individual vehicle categories with respect to the continuous measurement period at the location; **C** - correction factor and **n** - the total number of vehicle categories at the observed location.

The days and time periods for measuring noise levels can be randomly selected, or predefined. When the goal is to determine critical noise levels, the possible sources of data for selecting time periods are:

- Preliminary measurements, if any, and available data.
- Empirically, or based on other findings, whose level of reliability has not been explicitly demonstrated.
- Statistical methods, whose theoretical assumptions have been applied in practice and in cases of solving similar problems [53].
- Available applications, such as the Google Traffic application, which is based on the crowdsensing method of data collection. It provides data through the GPS function of mobile devices, recording the trajectories and speeds of owners of available mobile devices at observed location.

6.1. Description of location, day, interval and length of measurement

The proposed method for assessing the criticality of noise pollution was verified by conducting an experiment at five locations in the city centre of Belgrade: Bogoslovija, Bulevar Oslobodjenja, Studentski grad, Vojvode Stepe and Jove Ilića street.

The cumulative noise coefficients were calculated for all chosen locations. We document the implementation of the proposed method in detail using the example of the location Bogoslovija.

Description of location, day, interval and length of measurement for the location Bogoslovija are:

1. Crossroads type: roundabout
2. Road type: Gateway
3. Speed limit: 30−50 km/h
4. No traffic lights: (uncontrolled intersections, without signals, stop-controlled intersections with one or more "STOP" signs)
5. Pedestrian crossings 5−10 m from the roundabout
6. City traffic stops at 20−30 m from the roundabout
7. There are no sound barriers
8. Estimated duration of peak traffic: 5h
9. Recommended measurement days: Monday to Friday (the assumption is that Saturday and Sunday are not critical)
10. Recommended measurement time: 7.30–8.30 h and 15−18 h (source: Google Traffic application)
11. Prevailing influences on the criticality rank: the tram terminus.

Because the traffic data doesn't exist or is not public for the location Bogoslovija, we have selected the critical time intervals for noise measurement based on the data collected by the Google Traffic application. Available data are shown in the Table 2.

Based on the available data, the highest traffic density at this location is in periods between 7−9 h and 15−18 h. The specified period corresponds to the reference time interval: day. Data shows that Saturday and Sunday are not critical, so due to limited resources, these measurement days are not necessary.

An example of the calculation of the cumulative coefficient **R** for the location Bogoslovija is shown in the Table 3.

Table 3 presents in detail the calculations of the individual impacts represented by the vehicle category on the resulting, cumulative noise rank of the target location. Column 1 contains the categories of represented vehicles. Column 2 shows the highest legal noise levels of the represented vehicle categories listed in column 1. Column 3 shows the relative maximum noise level of the represented vehicle categories, calculated in relation to the noise produced in this case by trams (80 dB). Column 4 shows the total participation of vehicles represented in the 24-day cycle, and column 5 shows participation relative to the length of day (24 h). Finally, the individual and cumulative results are presented in column 6. Individual rankings of represented vehicles show that despite the participation of trams, motor vehicles have the highest criticality rank (M.1.1-1.2) because they traffic all day. The aggregate cumulative coefficient of a vehicle is the sum of the individual ranks: 1.644. Corrective coefficients are not included, C = 1 is adopted, so the final, total coefficient at the location is R = 1.644.

Using the same methodology, based on the available input data and assumptions, the criticality coefficients of all other target locations were calculated and are shown in Table 4.

By comparing the estimated criticality factors (Table 4, column 3), the first three locations appear to be significantly more exposed to noise compared to the remaining. The reason is the participation of noisier vehicle categories, especially in the case of locations with tram traffic 1, 2 and 3. The estimated criticality factors are significantly lower in the case of locations 4 and 5. Location 4 is a city boulevard with heavy passenger car traffic and a low proportion of city buses, and location 6 is a residential street, used exclusively by passenger vehicles.

The estimated criticality factors served to create a list of measurement priorities and to subsequently check the applicability of the proposed methodology.

7. Analysis of results

7.1. Exploratory analysis

According to the national Regulation on noise indicators, limit values, methods for assessing noise, disturbance and adverse effects of environmental noise [17], the permissible level of noise in the city centre, zones along highways and city roads is 65 dB.

The measurements were done in the period May 8–28, 2019, every day in the selected periods of the day. Data was collected using the described mobile application, by students of Faculty of organizational sciences, University of Belgrade. Before the data collection process started, the accuracy of the developed mobile application for noise measuring was checked. The application was installed on students' phones, and a few measurements were performed using the developed app. In addition, the noise was measured using another sound metering app available for Android devices. The discrepancies in measurements were lower than 5 %, which was acceptable for further research. The dataset is available through the API of the developed system, at the following link: https://crowdsensing.elab.fon.bg.ac.rs/api/data-protected/f0b15414a63813e2d7f29e53d5d8d68d?page=1&limit=10&from=2019-05-08&to=2019-05-10

The dataset can be selected by setting the parameters limit, from and to, in the given link.

There were 4251 measurements in total: 109 measurements per day,

Table 2
Recommended time and duration of measurements at location Bogoslovija.

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Measurement periods	8–8.30 h 15.30–18 h	7–9 h 15–18 h	7–9 h 16–18 h	7–9 h 15–18 h	7–9 h 15–18 h	14.30–15.30 h	–
Recommended measurement duration	4 h	5 h	4 h	5 h	5 h	1 h	–

Table 3
Calculation of the cumulative coefficient R for the location: Bogoslovija.

Presented categories of vehicles [57] (measurement periods are: 7–9 h and 15–18 h)	Max legal noise level (dB)	Relative noise level in relation to max	t (h)	Relative duration	Individual rank
1	2	3	4	5	6
motor vehicles (M.1.1-1.2)	68–69	68.5/80 = 0.856	24 h	24/24 = 1	0.856*1 = 0.856
buses (M2.1-4, M3.1-2)	70–73 74–76	73/80 = 0.913	5h	5/24 = 0.21 (based on the timetable)	0.913*0.21 = 0.192
trams(T)	80	80/80 = 1	5h	5/24 = 0.21 (based on the timetable)	1*0.21 = 0.21
delivery vehicles and trucks(N1.1-2, N2.1-3, N3-1-2)	69–78 73.5	73.5/80 = 0.919	10 h	10/24 = 0.42	0.919*0.42 = 0.386
Cumulative noise coefficient based on vehicle categories					**Σ = 1.644**
Other influences					**C = 1**
Adjusted coefficient due to other influences					**1.644*1**
Total noise coefficient at the location					**R = 1.644**

Table 4
Estimated criticality coefficients of chosen location for the experiment.

ID	Location	Location type	Estimated criticality coefficient (R)
1	Location 1 Bogoslovija	roundabout	1.644
2	Location 2 Studentski grad	busy city street	1.191
3	Location 3 Vojvode Stepe	busy city street	1.136
4	Location 4 Bulevar Oslobodjenja	city boulevard	0.721
5	Location 5 Jove Ilića	residential street	0.527

76 measurements in the periods 08–10 h and 16–18 h. Data was collected from different microlocations in the city of Belgrade, Serbia. Most of the measurements were done through participatory sensing at the selected microlocations shown in Table 4, but the sample included a number of measurements done through opportunistic sensing. The

Table 5
Number of measurements per location and per day period.

Location	Location type	No. of measurements			
		total	06–18 h	18–22 h	22–06 h
Location 1 Bogoslovija	busy city street	434	387	47	0
Location 2 Studentski grad	residential street	295	268	25	2
Location 3 Vojvode Stepe	city boulevard	337	263	59	15
Location 4 Bulevar Oslobodjenja	busy city street	723	598	90	35
Location 5 Jove Ilića	roundabout	961	843	93	25
Other		1501	1204	214	83

outliers were corrected; all the values above 95 percentile were assigned the values of the 95 percentile (Table 5).

Fig. 5 shows the map of Belgrade with all the measurements. Red circles on the map present locations with the measured noise level above 60 dB, orange circles represent noise level between 30 and 60 dB, while green circles present noise below 30 dB.

Noise heatmap is presented in Fig. 6. Red areas present high noise levels, orange areas are for noise level within the allowed values, and green colour shows low noisy areas.

Further analysis has been done for the five selected locations. Estimated criticality coefficients for the selected locations are presented in Table 6, as well as means and maximal values of the measured noise.

The measured mean values show that the average noise level is within the normal limit. However, the maximal measured values show that there was measured noise above the allowed limit on all the locations. Locations 3, 4 and 5 have high maximal values, more than 30 dB higher than the prescribed limit. Results also show that means for rush hours (8–10 h and 16–18 h) are higher than daily means for all locations. The obtained measured results generally correspond to the estimated criticality coefficients. The main difference between the estimated ranks and the measured values is for locations 2 and 3. Location 2 has lower measured noise values than expected. The cause for this result may be the complexity of this location, which is near the highway and heavy crossroads but includes blocks of residential buildings. It is possible that the measurements were done on microlocations closer to residential areas or that the criticality coefficient was not well estimated.

The comparative results of the performed measurements and estimated criticality coefficients leads to the conclusion that the proposed approach can be used for planning noise pollution measurements. This is especially applicable for measuring noise pollution on microlocations where there are no stations for official noise monitoring, or when the resources needed for determining the critical microlocations are insufficient.

7.2. Statistical analysis - Principal component analysis

Further analysis was performed by considering the frequency spectra of the collected measurements. The dataset (Table 7) has 650 variables and 4251 measurements in total, so the dimensionality reduction is necessary for further analysis.

The amplitudes of frequencies decrease as the frequency increases (Fig. 7), and at higher frequencies, the amplitudes are near zero. The highest amplitudes are at frequencies around 16 Hz, as well as the highest deviations. Having in mind that the highest amplitudes and deviations were measured for the frequencies up to 100 Hz, only measurements at these frequencies were considered in further analysis. Fig. 8 shows amplitudes and deviations for frequencies 0–100 Hz.

The correlation of measured values at frequencies 0–100 Hz is shown in Fig. 8. Diagonal elements are frequencies 0–100 Hz. Light colours in Fig. 8 show high correlations, while the dark colour represents low correlations. Frequencies 5 Hz and 10 Hz are highly correlated, ($\rho = 0.93$, light colours in the upper left corner) while the low correlations were observed between these frequencies and all the other frequencies (dark colours in Fig. 9).

Further analysis was done using the method of principal component analysis (PCA) [58]. This is a multivariate analysis whose goal is to reduce the dimensionality of the dataset while keeping as much variability as possible. Values of Kaiser-Meyer-Olkin [59] (KMO = 0.961)

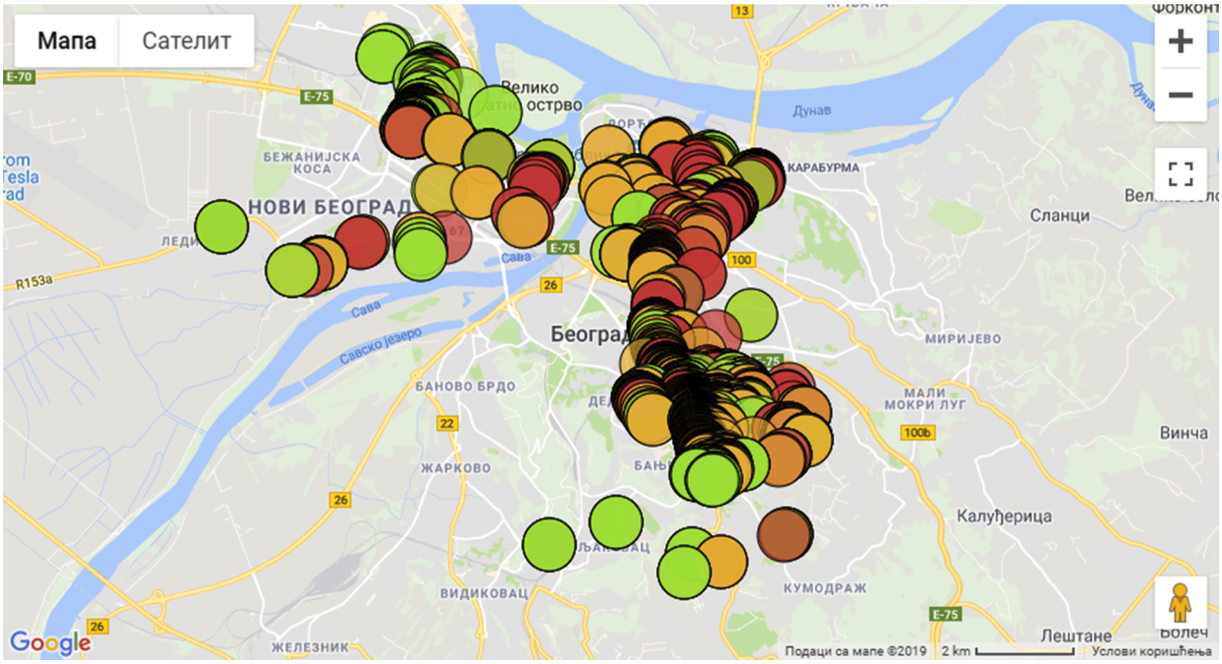

Fig. 5. Map of Belgrade showing all measurements. (For interpretation of the references to colour in this figure text, the reader is referred to the web version of this article.)

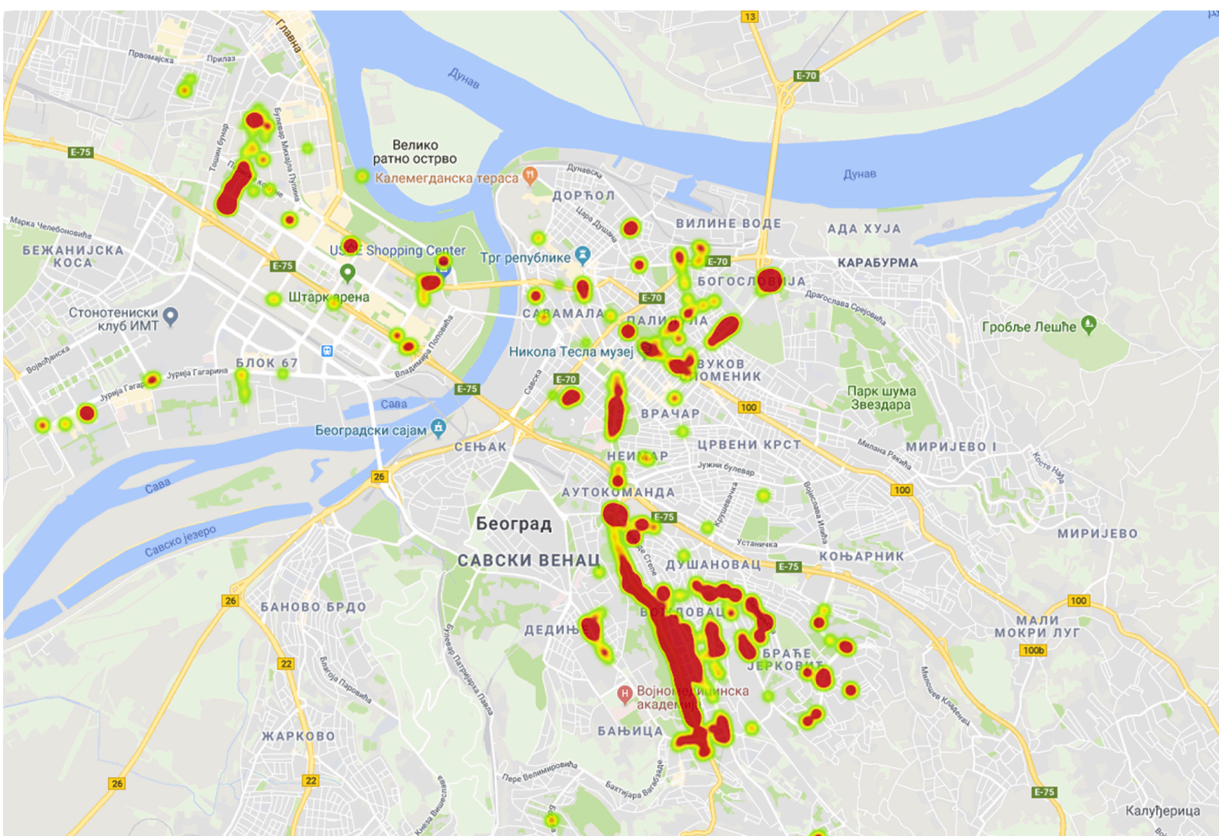

Fig. 6. Noise heatmap. (For interpretation of the references to colour in this figure text, the reader is referred to the web version of this article.)

and Bartlett sphericity test (p = 0.00 < *0.01)* are satisfactory, so the PCA can be applied for this dataset. Using the Kaiser criterion, two principal components were identified, and they explain 95 % of the variability in data.

From the scree plot (Fig. 10) [58,60], we can conclude that the number of two components is adequate. This method considers characteristic square roots of corresponding components and then looks for the greatest inflection of the curve. We choose components left of the elbow, in this case, the inflection is on number 3, so 2 components are adequate for further analysis.

Table 6
Locations, relative criticality coefficients, noise means, and maximal values.

ID	Location	Location type	Relative criticality coefficients	Means (in DB)	Means for periods 8–10 h and 16–18 h (in DB)	Maximal measured noise (in DB)
1	Location 1 Bogoslovija	roundabout	1.644/1.644 = 1	45.3	48	69
2	Location 2 Studentski grad	busy city street	1.191/1.644 = 0.724	40.5	42	73
3	Location 3 Vojvode Stepe	busy city street	1.136/1.644 = 0.691	43.3	49	102
4	Location 4 Bulevar Oslobodjenja	city boulevard	0.721/1.644 = 0.439	35.4	38	101
5	Location 5 Jove Ilića	residential street	0.527/1.644 = 0.321	35.5	39	104

Table 7
Dataset description.

Variable	Type	Description
ID	Int	The ID of each measurement
Location	Factor(r) – 143lvl	Location of measurement. There were 143 identified locations.
Avg	Num	The average value of measured noise in dB
Max	Num	Max value of measured noise in dB
Lat	Num	Latitude
Lon	Num	Longitude
Date	Date, format: "2019-04-28"	Date of measurement
Day	Factor – 7lvl	Day in a week
Time	Chr	Time of measurement
PeriodDay	Factor – 4lvl	Morning, afternoon, evening, night
Frequencies 0–3195	Num	Measured value for frequencies 0–3195

Results obtained with PCA using the Varimax orthogonal rotation (Fig. 11) show that one component includes frequencies 0, 5, 10, 15 and 20 Hz, while all the other frequencies belong to the second component.

The obtained results show that further analysis of the data can be done by analysing the two identified components. In this way, the dimensions of the dataset were reduced, and there is a lower probability of colinearity. In the further text, we analyse the identified components for the selected locations.

7.3. Data analysis for the Location 2 - Studentski grad

Mean values and deviations for the frequencies in the first component for days in the weak for the location Studentski grad are presented in Fig. 12. The sample size is n = 295.

Fig. 12 shows that mean values seem lower on Thursdays and Saturdays, compared to the other days in the weak. In addition, figure shows high deviations within each day.

Since the sample size is n = 295, using the central limit theorem, we can assume the normal distribution of data, and apply ANOVA for testing the differences in variances [61]. Levine test of homogeneity of variance gives p-value $0.00028 < 0.05$, so we conclude that variances are not homogenous.

ANOVA results $F(6,288) = 2.312$ ($p = 0.049 < 0.05$) lead to the conclusion that there is a statistically significant difference of

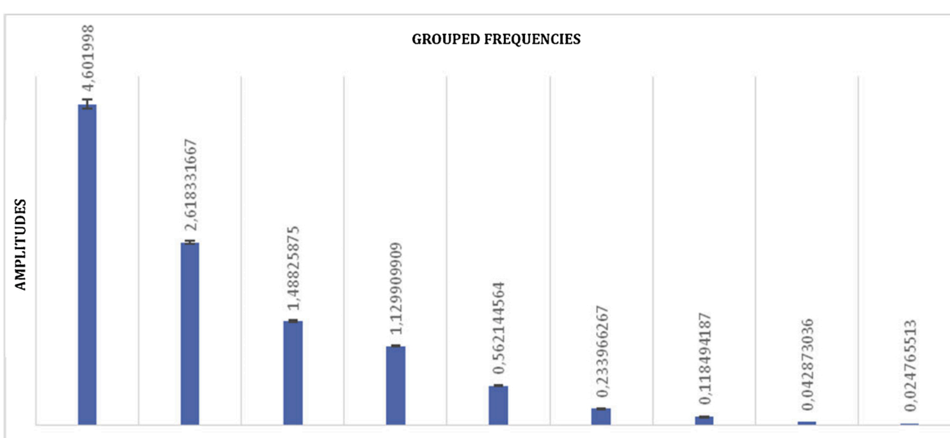

Fig. 7. Grouped frequencies and their amplitudes (X axis: grouped frequencies in Hz; Y-axis: amplitude in dB).

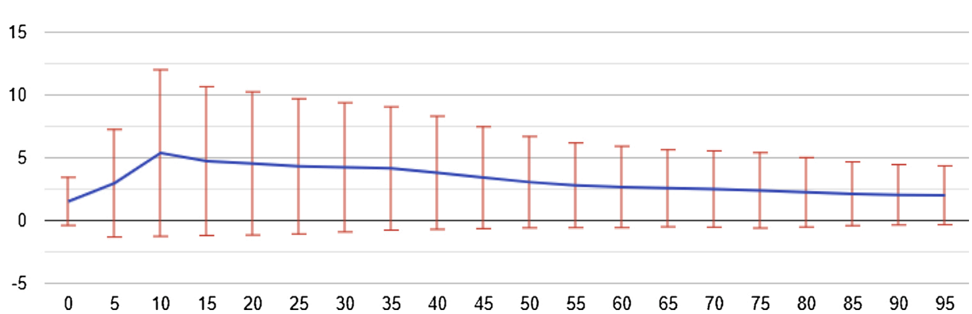

Fig. 8. Amplitudes and deviations for 0–95 Hz (X axis: frequencies in Hz; Y-axis: amplitude and deviations).

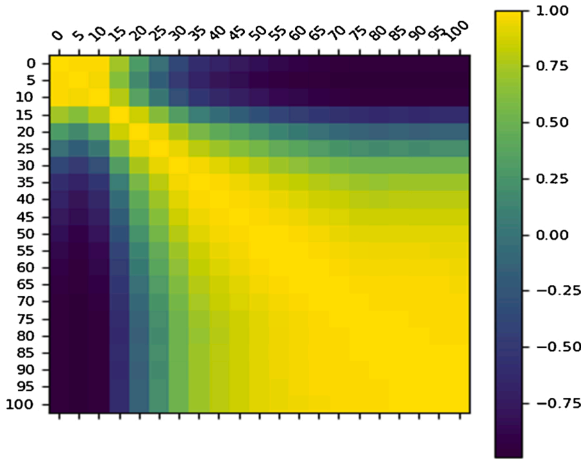

Fig. 9. Correlation matrix for frequencies 0–100 Hz.

frequencies for days in a weak. Post-hoc analysis was done using the Bonferroni test [62], and it shows that there is a statistical difference between values measured on Mondays and Thursdays ($p = 0.0066$), Mondays and Saturdays ($p = 0.0112$), Thursdays and Fridays ($p = 0.0168$) and Fridays and Saturdays ($p = 0.0259$). The measured noise on location Studentski grad is higher on Mondays and Fridays, comparing to Thursdays and Saturdays.

7.4. Data analysis for the Location 3 - Vojvode Stepe on Mondays

For the location Vojvode Stepe, the highest frequencies were measured on Mondays, so further analysis can reveal which periods of the day are the noisiest.

Analysis of variance (ANOVA) shows that there is a statistically significant difference between the mean values measured in each period of the day. The post-hoc analysis shows that there is a statistically significant difference between periods 1 and 2, and periods 1 and 3. The highest level of noise was measured in the period 6−18 h, while the noise was significantly lower after 6 pm (Fig. 13).

7.5. K-means clustering

In further analysis, we perform the cluster analysis in order to find typical clusters of noise measurements. Clustering was done using the k-means algorithm [58]. The input to this algorithm includes observations and the number of clusters. The algorithm finds the centroids of clusters and classifies all the observations into the closest cluster. The optimal number of clusters can be determined using the elbow method (Fig. 14).

Fig. 14 shows two inflections, at values 3 and 4. For further analysis, we opted out for 3 clusters. Fig. 15 shows the results of clustering. Table 8 shows the number of measurements in each cluster.

The main conclusions from the cluster analysis are:

- Cluster 2 (green cluster) is the cluster with the lowest noise. The highest number of measurements at the location *Jove Ilića* (around 69 %) belongs to this cluster. A relatively high number of measurements for the location *Bogoslovija* is also classified in this cluster. Further analysis would be necessary to determine what the exact similarities between the noise characteristics of these two locations are.
- Cluster 3 (blue cluster) is the cluster with medium noise. The highest number of measurements classified in this cluster comes from the location *Bulevar Oslobodjenja*. However, measurements from the location *Bulevar Oslobodjenja* almost equally belong to clusters 1 and 3. Dispersion of measurements from one location into different clusters is consistent with the previous conclusion that there are differences in the noise measured on different weekdays or different

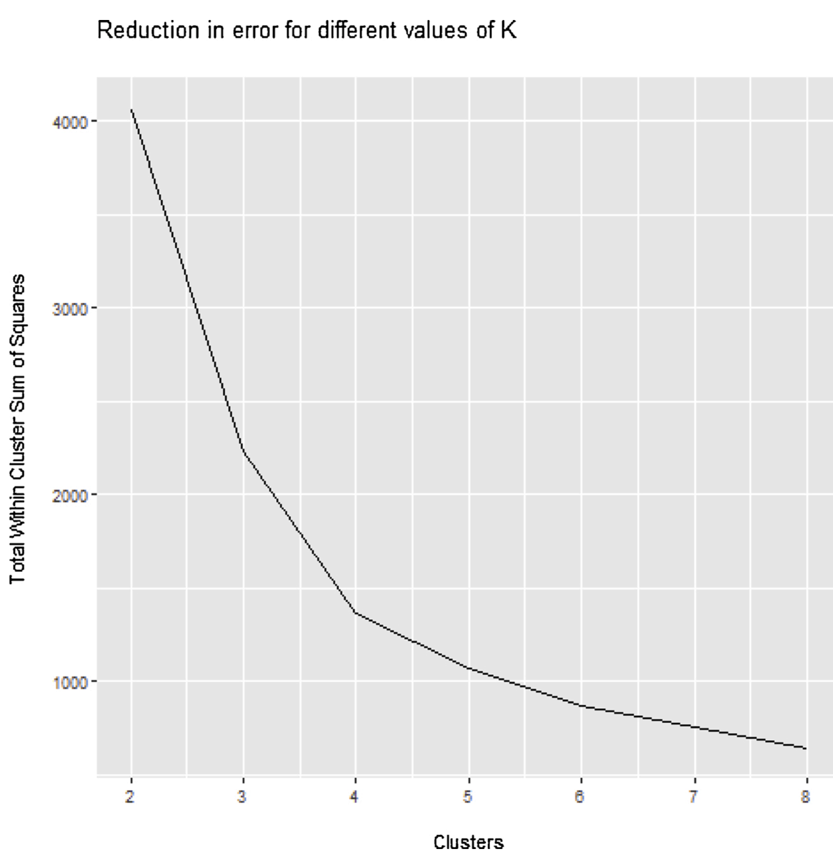

Fig. 10. Scree Plot - Elbow method (X axis: number of clusters; Y-axis: sum of squares within cluster).

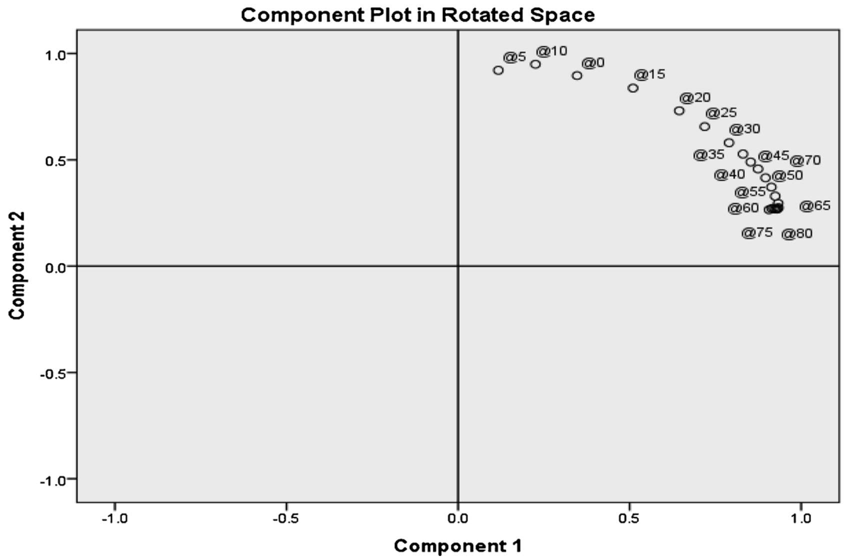

Fig. 11. PCA results.

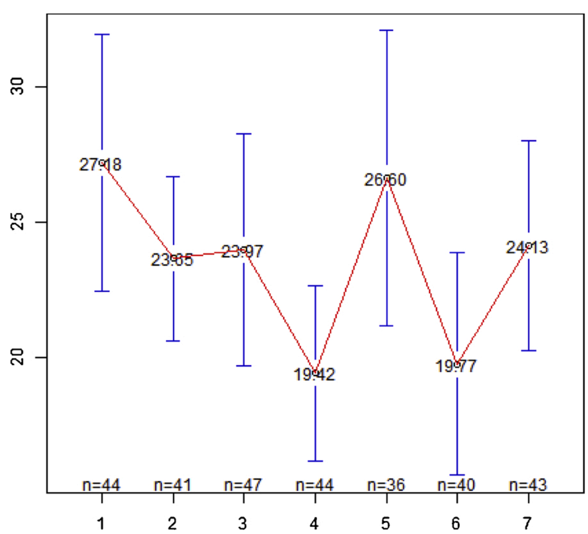

Fig. 12. Mean values and deviations for the frequencies in the first component for days in the weak for the location Studentski grad (X-axis: numbers 1–7 represent Monday to Sunday; Y-axis: mean values and deviations).

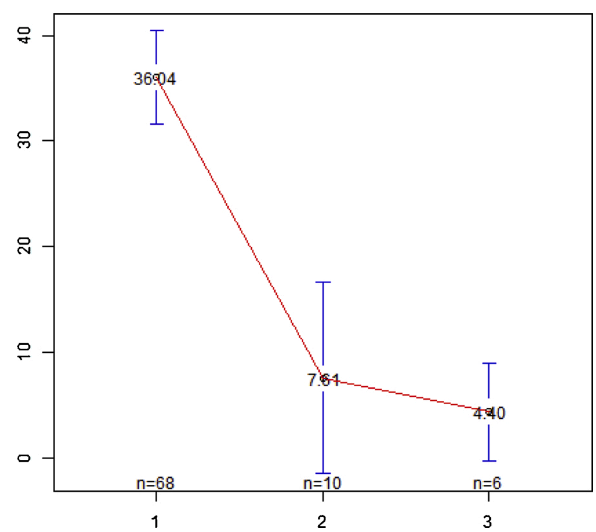

Fig. 13. Mean values of frequencies at location Vojvode Stepe on Mondays (X-axis: periods 1, 2 and 3 represent periods in a day 6–18 h, 18–22 h and 22–6 h, respectively. Y-axis: mean values and deviations).

periods of the day. The numbers of observations at this location classified into cluster 3 per weekday are 49, 28, 27, 41, 19, 20, 60 (Monday to Sunday, respectively). Sunday at *Bulevar Oslobodjenja* is a day with the lowest noise, so it is expected that the most measurements from this day would be classified in cluster 3.

- Cluster 1 (red cluster) is the cluster with the highest noise. The most observations belonging to this cluster come from the location *Bulevar Oslobodjenja,* but there is also a number of observations from locations *Vojvode Stepe* and *Bogoslovija*. All these locations show differences in the levels of noise measured in different periods of the day and on different days of a week.

8. Discussion and conclusion

This paper presents a mobile crowdsensing system to monitor noise pollution in the city of Belgrade as well as recommendations for possible applications in other cities that are working on introducing new smart services. Noise pollution is one of the problems that today's urban entities are facing while trying to ensure acceptable community functioning and healthy environment. The older city infrastructures, planned at a time without today's heavy traffic, are most often under threat. As noise pollution is widespread throughout the city, it is difficult to solve the problem at the same time and immediately throughout the urban area. Therefore, the first step in taking the necessary actions to reduce noise levels to acceptable limits may be based on the estimated criticality levels at the target locations.

At estimated critical locations, we applied the system that enables participatory and opportunistic collection of noise data on micro-locations using mobile phones. Thousands of users can take noise measurements, and thus generate large amounts of data. As such, this system requires corresponding big data infrastructure capable of scaling and real-time analysis. The used technologies (mobile, IoT, cloud and big data) have already been identified as the main enablers for the future environmental applications [63]. The goal of the conducted experiment was to evaluate the developed system and to analyse the possibilities for developing adequate decision support based on the collected data.

Comparing to the other solutions presented in the literature, the presented work brings novelty in the research field which can be seen

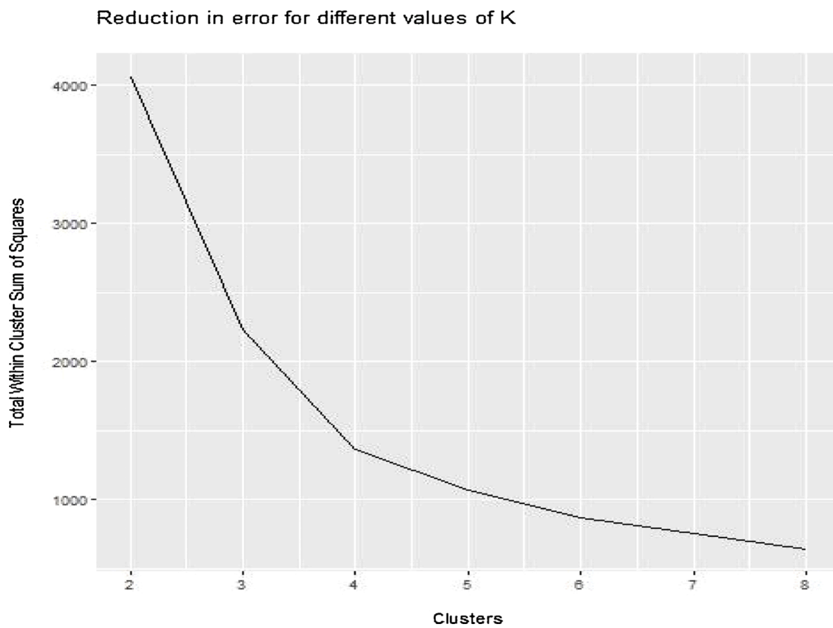

Fig. 14. Elbow method (X axis: number of clusters; Y-axis: sum of squares within cluster).

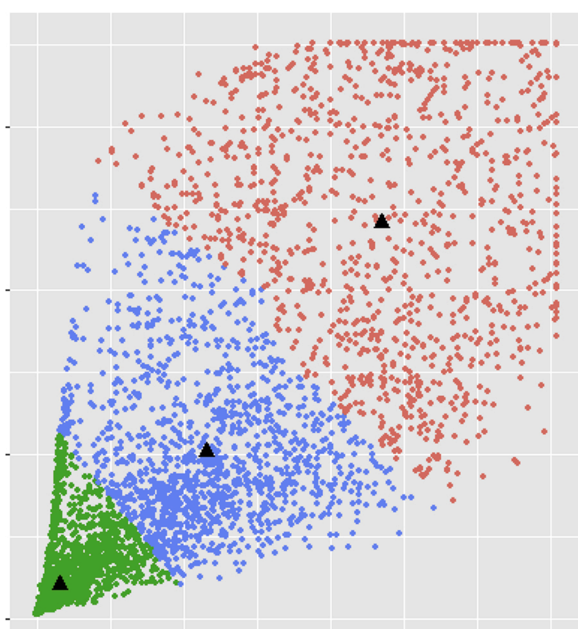

Fig. 15. Model with 3 clusters (X-axis: frequencies 0–20 Hz. Y-axis: frequencies 25–100 Hz).

Table 8
Number of measurements per cluster.

Location	C1(red)	C2(green)	C3(blue)
Location 1 - Bogoslovija	114	200	120
Location 2 - Studentski grad	35	72	188
Location 3 - Vojvode Stepe	134	114	89
Location 4 - Bulevar Oslobodjenja	278	196	249
Location 5 - Jove Ilića	103	663	195

through the following advantages. First of all, the developed system is based on open source technologies and therefore can be easily customized to the project's needs and integrated with other components. Secondly, the presented approach includes a methodology for selecting microlocations for noise measuring, enabling the crowdsensing process to be directed, which is expected to lead to usable conclusions. Then, the experimental part is based on a relatively high number of measurements and presents a few cases of data analysis and decision support, which lack in most of the papers present in the literature. Finally, the system was designed to be scalable, and it can easily be adapted to different contexts [64] and cities of all sizes.

When considering a wider application of the developed system, the following implications can be identified:

- Since it is based on mobile technologies, the developed system is more adaptive and available to different stakeholders, compared to stationary noise measuring. This can provide more accurate data about noise on the specific microlocations, not typically covered by stationary measuring. The accuracy is not achieved on the level of a measuring device, but by the high number of measurements and data analysis.
- In our experiment, the participants were student volunteers. However, the proposed system can be made available to all interested parties, and allow them to collect noise data on locations of interest. Residents can participate in opportunistic crowdsensing and collect data on different locations, or they can perform measurements in their neighbourhoods, and obtain data about noise pollution for specific microlocations. The collected data can serve as an indicator and a potential proof of increased noise pollution in a specific neighbourhood, therefore alerting the local government into taking the necessary steps.
- The traditional urban noise measurement techniques are expensive and can be applied only on major roads, railways and airports. Although the proposed system can be used as a standalone, its full potential could be achieved by its integration with official systems for noise measuring and mapping, at a low cost. The developed system could provide officials with additional information, possibilities for data analysis, decision support in the detection of noise pollution trends, and early detection of noise pollution on microlocations.
- Additional value is that data collected within this system can be provided as real-time open data. This would lead to higher transparency in smart cities and help citizens decide on many different matters, such as when deciding on the location of their future

apartment. Furthermore, these data could be valuable in the urban planning and deciding in the process of building residential parts of the city.

- After uncovering potential critical locations, followed by crowdsensing verification, IoT technology can be used alongside neural networks to monitor and predict noise pollution levels online. Installed IoT devices may provide a large quantity of data at different time intervals and could initiate the available actions to reduce the noise level at the observed locations [65].

During the experimental phase of the research, a few problems have been identified. First, the availability of the volunteers who would participate in the research was limited. To overcome this constraint and obtain a significant amount of representative measurements, we have developed a methodology for selecting the microlocations and periods where and when the measurements would take place. Since it was not possible to obtain official data on participants in traffic, our methodology is based on creating traffic patterns based on the configurations of the microlocations and traffic regulations for each of them. Moreover, during the execution of our experiment, we had no data on previous measurements and peak traffic periods. So we used the Google Traffic application's open data. In response to this issue, we believe it is useful to use the CrowdSenSim simulator, though the current edition simulates pedestrian mobility in urban areas [66]. Meanwhile, the simulator authors announced that they would supplement the current application scenarios with models of vehicle involvement in traffic flows. In this case, we expect the application of this simulator to offset some of the missing data we use in our research.

The results of the performed analysis have confirmed that the estimated coefficients mainly corresponded to the data gathered in the experiment. However, in the case of a complex location of Studentski grad, it is necessary to repeat measurements, using strictly predefined tracks.

Another limitation of the presented approach is related to the potential misuse of the application. Users have the possibility to input bad data by recording fabricated sounds. In order to solve this problem, additional spectral analysis can be used to identify data that does not fit the noise profile of the microlocation, and recordings could be compared to those made by other users.

Finally, the technical characteristics of the presented approach may influence the accuracy of the results. Having in mind that the crowdsensing is always based on various users' devices with different characteristics, it is likely that there are measurements with significant errors, some of which may pass undetected in the analysis phase. However, the goal of the developed approach is not to achieve a high level of accuracy on the base of individual device, but to enable gathering enough data through crowdsensing to achieve acceptable level of accuracy. Additionally, the characteristics of mobile phones' microphones may result in measured noise being lower than the real one. For the purpose of this research, we didn't consider this to be a problem. If the noise level above the allowed is detected, the real noise can only be higher, so still above the allowed value.

The system was implemented in the city of Belgrade and the results presented are important from a local perspective. However, the method of estimating critical locations is adaptable, meaning that it is possible to add new sources as well as different noise parameters. The existing system parameters for micro locations are common throughout urban environments, and are easily applied in other cities. Some of the common parameters are: crossroads types, road types, speed limits, traffic lights, distance of pedestrian crossings, distance of city traffic stops, existence of sound barriers, traffic intensity, peak traffic hours and other prevailing influences. Additionally, the model provides five criteria based on criticality coefficients for location selection. These criteria can be utilized to further identify critical or interesting locations based on measured data. As a result, the system and its underlying concepts can be used to detect and analyse noise pollution in other cities and urban areas.

One of the drawbacks of the realized experiment lies in the fact that the measurements were taken in a period of three weeks in May, so the presented results may not be generalizable for the whole year. However, this paper does not aim to provide a full analysis of noise data at the selected locations, but rather to demonstrate the capabilities of the developed system, and it's potential to relevant decision-makers. The same argument applies for the selection of the evaluation context. Another potential drawback is related to the monitoring of users mobile phones in regards to the energy cost and effects of the monitoring app. Despite insufficient monitoring, the students who participated in the data collection reported no issues regarding their batteries or any other problems with performance. Having in mind that Android devices use ARM processors with hardware support for floating-point operations in double-precision arithmetic, the FFT is not expected to cause significant energy consumption.

Based on the experience gained through the described research, several future work directions can be identified. The accuracy of selecting the microlocations for participatory crowdsensing relies on the quality of the available data. For example, in the case of complex microlocations, such as Studentski grad in our case, greater accuracy could be achieved by defining specific paths where the measurements should be done. This could be achieved by giving participant-specific GPS tracks and monitoring their movement during the measuring. Having in mind that it is not realistic to have a sufficient number of participants at all times, the optimal balance of participatory and opportunistic crowdsensing needs to be further researched and formulated. In addition, future work will be directed towards improving all the components of the proposed platform. Energy costs for participants joining the campaign will be measured, and the mobile application will be improved regarding the energy consumption. Finally, further research will be oriented towards developing a high-quality decision support system for crowdsourcing noise analysis based on deep learning and artificial intelligence.

CRediT authorship contribution statement

Ivan Jezdović: Data curation, Formal analysis, Investigation, Resources, Software, Visualization, Writing - original draft. **Snežana Popović:** Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing - original draft. **Miloš Radenković:** Data curation, Formal analysis, Investigation, Software, Validation, Writing - original draft. **Aleksandra Labus:** Conceptualization, Methodology, Resources, Validation, Writing - review & editing. **Zorica Bogdanović:** Conceptualization, Methodology, Project administration, Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors report no declarations of interest.

Acknowledgements

Authors are thankful to Ministry of Education, Science and Technological Development, Republic of Serbia, grant no. 174031.

References

[1] G. Somasundaram, R. Sivalingam, V. Morellas, N. Papanikolopoulos, Classification and counting of composite objects in traffic scenes using global and local image analysis, IEEE trans. Intell. Transp. Syst. 14 (2013) 69–81, https://doi.org/10.1109/TITS.2012.2209877.

[2] P.H.T. Zannin, M.S. Engel, P.E.K. Fiedler, F. Bunn, Characterization of environmental noise based on noise measurements, noise mapping and interviews: a case study at a university campus in Brazil, Cities 31 (2013) 317–327, https://doi.org/10.1016/j.cities.2012.09.008.

[3] Control of Noise Emissions Guidelines, 2017.

[4] Noise Emission by Outdoor Equipment, 2016.

[5] P.H.T. Zannin, F.B. Diniz, W.A. Barbosa, Environmental noise pollution in the city of Curitiba, Brazil, Appl. Acoust. 63 (2002) 351–358, https://doi.org/10.1016/S0003-682X(01)00052-4.

[6] A. Calixto, F.B. Diniz, P.H.T. Zannin, The statistical modeling of road traffic noise in an urban setting, Cities 20 (2003) 23–29, https://doi.org/10.1016/S0264-2751(02)00093-8.

[7] Y.R. Chew, B.S. Wu, A soundscape approach to analyze traffic noise in the city of Taipei, Taiwan, Comput. Environ. Urban Syst. 59 (2016) 78–85, https://doi.org/10.1016/j.compenvurbsys.2016.05.002.

[8] "Sl. glasnik RS" br. 72/2010, Pravilnik o metodama merenja buke, sadržini i obimu izveštaja o merenju buke, Beograd, 2010.

[9] "Sl. glasnik RS" br. 72/2010, Pravilnik o metodologiji za određivanje akustičkih zona, Beograd, 2010.

[10] E. D'Hondt, M. Stevens, A. Jacobs, Participatory noise mapping works! An evaluation of participatory sensing as an alternative to standard techniques for environmental monitoring, Pervasive Mob. Comput. 9 (2013) 681–694, https://doi.org/10.1016/j.pmcj.2012.09.002.

[11] X. Li, D.W. Goldberg, Toward a mobile crowdsensing system for road surface assessment, Comput. Environ. Urban Syst. 69 (2018) 51–62, https://doi.org/10.1016/j.compenvurbsys.2017.12.005.

[12] A. Capponi, C. Fiandrino, B. Kantarci, L. Foschini, D. Kliazovich, P. Bouvry, A survey on mobile crowdsensing systems: challenges, solutions, and opportunities, IEEE Commun. Surv. Tutorials 21 (2019) 2419–2465, https://doi.org/10.1109/COMST.2019.2914030.

[13] Y. Liu, L. Kong, G. Chen, Data-oriented mobile crowdsensing: a comprehensive survey, IEEE Commun. Surv. Tutorials 21 (2019) 2849–2885, https://doi.org/10.1109/COMST.2019.2910855.

[14] Zakon o zaštiti od buke u životnoj sredini, 2010. Službeni Glas.

[15] D. Offenhuber, S. Auinger, S. Seitinger, R. Muijs, Los Angeles noise array—planning and design lessons from a noise sensing network, Environ. Plan. B Urban Anal. City Sci. 47 (4) (2018) 609–625, https://doi.org/10.1177/2399808318792901.

[16] W.M. Batko, B. Stępień, Type a standard uncertainty of long-term noise indicators, Arch. Acoust. 39 (2014) 25–36, https://doi.org/10.2478/aoa-2014-0004.

[17] Uredba o indikatorima buke, graničnim vrednostima, metodama za ocenjivanje buke, uznemiravanja i štetnih efekata buke u životnoj sredini, 2010. Službeni Glas.

[18] C. Pronello, C. Camusso, A review of transport noise indicators, Transp. Rev. 32 (2012) 599–628, https://doi.org/10.1080/01441647.2012.706332.

[19] D. Cvetković, M. Praščević, V. Stojanović, Merenje i ocena buke - Fizički parametri radne i životne sredine, XVI Jugosl. Konf. Sa Međunarodnim Učešćem Buka i Vib. (1998) 1–4.

[20] A.-M.O. Mohamed, E.K. Paleologos, F.M. Howari, Noise pollution and its impact on human health and the environment, Pollut. Assess. Sustain. Pract. Appl. Sci. Eng. (2021) 975–1026, https://doi.org/10.1016/b978-0-12-809582-9.00019-0. Elsevier.

[21] Julius O. Smith, Spectral Audio Signal Processing, W3K, Center for Computer Research in Music and Acoustics, Stanford University. Department of Music, 2011.

[22] K.R. Rao, D.N. Kim, J.J. Hwang, Fast Fourier Transform - Algorithms and Applications, Springer, 2010.

[23] L. Sanchez, L. Muñoz, J.A. Galache, P. Sotres, J.R. Santana, V. Gutierrez, R. Ramdhany, A. Gluhak, S. Krco, E. Theodoridis, D. Pfisterer, SmartSantander: IoT experimentation over a smart city testbed, Comput. Netw. 61 (2014) 217–238, https://doi.org/10.1016/j.bjp.2013.12.020.

[24] M. Zappatore, A. Longo, M.A. Bochicchio, Using mobile crowd sensing for noise monitoring in smart cities, 2016 Int. Multidiscip. Conf. Comput. Energy Sci. Split. 2016 (2016), https://doi.org/10.1109/SpliTech.2016.7555950.

[25] G. Singh, D. Bansal, S. Sofat, A smartphone based technique to monitor driving behavior using DTW and crowdsensing, Pervasive Mob. Comput. 40 (2017) 56–70, https://doi.org/10.1016/j.pmcj.2017.06.003.

[26] G. Cardone, L. Foschini, P. Bellavista, A. Corradi, C. Borcea, M. Talasila, R. Curtmola, Fostering participaction in smart cities: a geo-social crowdsensing platform, IEEE Commun. Mag. 51 (2013) 112–119, https://doi.org/10.1109/MCOM.2013.6525603.

[27] R.K. Rana, C.T. Chou, S.S. Kanhere, N. Bulusu, W. Hu, Ear-phone an end-to-end participatory urban noise mapping system, Proc. 9th ACM/IEEE Int. Conf. Inf. Process. Sens. Networks - IPSN' 10 (2010) 105–116, https://doi.org/10.1145/1791212.1791226. ACM Press, New York, New York, USA.

[28] E. Kanjo, NoiseSPY: a real-time mobile phone platform for urban noise monitoring and mapping, Mob. Netw. Appl. 15 (2010) 562–574, https://doi.org/10.1007/s11036-009-0217-y.

[29] M. Stevens, E. D'Hondt, Empowering Technologies for Environmental Participatory Sensing, Vrije Univ. Brussel, Brussels, Belgium, 2015.

[30] I. Schweizer, R. Artl, A. Schulz, F. Probst, M. Uhl Auser, NoiseMap -Real-time participatory noise maps, Second Int. Work. Sens. Appl. Mob. Phones (2011) 1–5.

[31] N. Maisonneuve, M. Stevens, M.E. Niessen, L. Steels, NoiseTube: Measuring and Mapping Noise Pollution with Mobile Phones, Springer, Berlin, Heidelberg, 2009, pp. 215–228, https://doi.org/10.1007/978-3-540-88351-7_16.

[32] M. Stevens, E.D. 'hondt, Crowdsourcing of pollution data using smartphones, Int. Conf. Entertain. Comput. (2012) 562–571.

[33] I.G. Martí, L.E. Rodríguez, M. Benedito, S. Trilles, A. Beltrán, L. Díaz, J. Huerta, Mobile Application for Noise Pollution Monitoring through Gamification Techniques, Springer, Berlin, Heidelberg, 2012, pp. 562–571, https://doi.org/10.1007/978-3-642-33542-6_74.

[34] S. Grubeša, A. Petošić, M. Suhanek, I. Đurek, Mobile crowdsensing accuracy for noise mapping in smart cities, Automatika 59 (2018) 286–293, https://doi.org/10.1080/00051144.2018.1534927.

[35] E. Murphy, E.A. King, Testing the accuracy of smartphones and sound level meter applications for measuring environmental noise, Appl. Acoust. 106 (2016) 16–22, https://doi.org/10.1016/j.apacoust.2015.12.012.

[36] P. Aumond, C. Lavandier, C. Ribeiro, E.G. Boix, K. Kambona, E. D'Hondt, P. Delaitre, A study of the accuracy of mobile technology for measuring urban noise pollution in large scale participatory sensing campaigns, Appl. Acoust. 117 (2017) 219–226, https://doi.org/10.1016/j.apacoust.2016.07.011.

[37] J. Zuo, H. Xia, S. Liu, Y. Qiao, Mapping urban environmental noise using smartphones, Sensors 16 (2016) 1692, https://doi.org/10.3390/s16101692.

[38] C. Beyers, Calibration methodologies and the accuracy of acoustic data, in: C. Beyer (Ed.), INTER-NOISE NOISE-CON Congr. Conf. Proc., 2014, pp. 3104–3111. Institute of Noise Control Engineering, Melbourne.

[39] J.M. Barrigón Morillas, D. Montes González, G. Rey Gozalo, A review of the measurement procedure of the ISO 1996 standard. Relationship with the European Noise Directive, Sci. Total Environ. 565 (2016) 595–606, https://doi.org/10.1016/j.scitotenv.2016.04.207.

[40] S. Reddy, M. Mun, J. Burke, D. Estrin, M. Hansen, M. Srivastava, Using mobile phones to determine transportation modes, ACM Trans. Sens. Netw. 6 (2010) 1–27, https://doi.org/10.1145/1689239.1689243.

[41] X. Hao, L. Xu, N. Lane, X. Liu, T. Moscibroda, Density-aware compressive CrowdSensing, IPSN2017 (2017) 29–40.

[42] S. Lin, J. Zhang, L. Ying, Crowdsensing for Spectrum discovery: a waze-inspired design via smartphone sensing, IEEE/ACM Trans. Netw. 28 (2020) 750–763, https://doi.org/10.1109/TNET.2020.2976927.

[43] Noise Nuisance and the Law, 2015.

[44] European Parliament and Council, Directive 2002/49/EC of 25 June 2002 relating to the assessment and management of environmental noise, Off. J. Eur. Commun. 45 (2002) 12–26.

[45] E. Murphy, E.A. King, Strategic environmental noise mapping: methodological issues concerning the implementation of the EU Environmental Noise Directive and their policy implications, Environ. Int. 36 (2010) 290–298, https://doi.org/10.1016/J.ENVINT.2009.11.006.

[46] K. Kaliski, E. Duncan, J. Cowan, Community and regional noise mapping in the United States, Sound Vib. (2007) 14–17.

[47] I. Jezdovic, S. Popovic, M. Radenkovic, A. Labus, Z. Bogdanovic, System for noise measurement in traffic in smart cities, InfoM Časopis Za Inf. Tehnol. i Multimedijalne Sist. 66 (2018) 12–19.

[48] H.R. Arkian, A. Diyanat, A. Pourkhalili, MIST: fog-based data analytics scheme with cost-efficient resource provisioning for IoT crowdsensing applications, J. Netw. Comput. Appl. 82 (2017) 152–165, https://doi.org/10.1016/j.jnca.2017.01.012.

[49] S. Garg, K.M. Lim, H.P. Lee, An averaging method for accurately calibrating smartphone microphones for environmental noise measurement, Appl. Acoust. 143 (2019) 222–228, https://doi.org/10.1016/j.apacoust.2018.08.013.

[50] A. Can, G. Guillaume, J. Picaut, Cross-calibration of participatory sensor networks for environmental noise mapping, Appl. Acoust. 110 (2016) 99–109, https://doi.org/10.1016/j.apacoust.2016.03.013.

[51] Flight - An extensible micro-framework for PHP, (n.d.). https://flightphp.com/ (Accessed 16 May 2021).

[52] R. Ganti, F. Ye, H. Lei, Mobile crowdsensing: current state and future challenges, IEEE Commun. Mag. 49 (2011) 32–39, https://doi.org/10.1109/MCOM.2011.6069707.

[53] H. Ma, D. Zhao, P. Yuan, Opportunities in mobile crowd sensing, IEEE Commun. Mag. 52 (2014) 29–35, https://doi.org/10.1109/MCOM.2014.6871666.

[54] N.D. Lane, S.B. Eisenman, M. Musolesi, E. Miluzzo, A.T. Campbell, Urban sensing systems: opportunistic or participatory? HotMobile 2008 9th Work. Mob. Comput. Syst. Appl. (2008) 11–16, https://doi.org/10.1145/1411759.1411763.

[55] S. Reddy, D. Estrin, M. Srivastava, Recruitment framework for participatory sensing data collections, Lect. Notes Comput. Sci. (Including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics) (2010) 138–155, https://doi.org/10.1007/978-3-642-12654-3_9.

[56] G. Forbes, Urban roadway classification before the design begins, in: Layout Funct. Classif. Differ. Paradig., TRB Circular E-C019: Urban Street Symposium, Dallas, 2000, pp. 1–8.

[57] Vehicle Categories, 2019. Online. https://ec.europa.eu/growth/sectors/automotive/vehicle-categories_en/. (Accessed 8 February 2019).

[58] G. James, D. Witten, T. Hastie, R. Tibshirani, An Introduction to Statistical Learning With Applications in R, 2013, https://doi.org/10.1007/978-1-4614-7138-7.

[59] B.D. Hill, Sequential Kaiser-Meyer-Olkin Procedure As an Alternative for Determining the Number of Factors in Common-Factor Analysis: a Monte Carlo Simulation, Oklahoma State University, 2011.

[60] L.R. Nelson, Some observations on the scree test, and on coefficient alpha, J. Educ. Res. Meas. 3 (2005) 1–17.

[61] M.J. Blanca, R. Alarcón, J. Arnau, R. Bono, R. Bendayan, Non-normal data: is ANOVA still a valid option? Psicothema 29 (2017) 552–557, https://doi.org/10.7334/psicothema2016.383.

[62] A. McCloskey, Bonferroni-based size-correction for nonstandard testing problems, J. Econom. 200 (2017) 17–35, https://doi.org/10.1016/j.jeconom.2017.05.001.

[63] C. Granell, D. Havlik, S. Schade, Z. Sabeur, C. Delaney, J. Pielorz, T. Usländer, P. Mazzetti, K. Schleidt, M. Kobernus, F. Havlik, N.R. Bodsberg, A. Berre, J.L. Mon, Future Internet technologies for environmental applications, Environ. Model. Softw. 78 (2016) 1–15, https://doi.org/10.1016/j.envsoft.2015.12.015.

[64] L. Baljak, N. Bojkovic, A. Labus, T. Naumovic, A. Maksimovic, A system for mobile crowdsensing vibration in public transportation, 2nd Int. Conf. Artif. Intell. Appl. Innov., Vrdnik, Serbia (2019) 30–34.
[65] X. Zhang, M. Zhao, R. Dong, Time-series prediction of environmental noise for urban iot based on long short-term memory recurrent neural network, Appl. Sci. 10 (2020) 1144, https://doi.org/10.3390/app10031144.
[66] C. Fiandrino, A. Capponi, G. Cacciatore, D. Kliazovich, U. Sorger, P. Bouvry, B. Kantarci, F. Granelli, S. Giordano, CrowdSenSim: a simulation platform for mobile crowdsensing in realistic urban environments, IEEE Access 5 (2017) 3490–3503, https://doi.org/10.1109/ACCESS.2017.2671678.