Visualization of Sensors' Data in Time Series Databases for Health Purposes

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Abstract

The increasing influx of information on pollutants that affect human health leads to collection of huge amounts of data that are recorded in many different formats, servers, for different types of pollutants, for different geographical locations, temporally arranged and most often recorded in time series formats. According to the Law on free access to public information, the institutions are obliged to publish all these data on different types of pollution on public websites and to make them available to the citizens. Institutions most often publish collected and stored data at locations where the measurement sensors are found and present them in visual formats for the current measured data for a certain pollutant, which are understandable to the citizens. Many applications can show at any time the values of pollutants at certain positions. In addition, summary analyzes can be made if the allowed limits for pollutants are known according to the Law on environmental protection. However, there is no organized effort to quantify their common impact on a person during their lifetime, i.e. to assess the risk for each individual depending on their health conditions, chronic disease, if any, or assessment of external pollutants – aero-exposures to the individual at one location over a period. Setting such a premise, especially if a prediction of outcomes could be made, would be very useful if these aero-exposomes were linked to the chronic disease from the patient's personal health record (PHR), particularly on the respiratory system. The risk assessment of residence in certain areas in a certain period, and the availability of this assessment to his doctor and to him personally, would be very useful because it would protect patient's health and give recommendations for avoiding locations in periods of stay in certain locations. In this paper, we are trying to give some guidance and propose a model for visual data analysis from time series with environmental data that should help in assessing the risk of residence in some locations at particular time. Data are obtained from measuring sensors, placed in the northwestern region of Republic of North Macedonia. The limits of permitted values of pollutants

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are taken into consideration, according to the Ministry of Environment and physical planning website, as well as data from patient's PHR who has been diagnosed with chronic diseases of obstructive respiratory system.

Keywords
Time series data visualization, visual data analysis, aero-exposome, chronic respiratory disease, aero-pollutants sensor's data

1. Introduction

Time-oriented data analysis is an important task in many applications and scenarios. In recent years, many different techniques have been used to visualize this type of data. This diversity makes it difficult for potential users to choose methods or tools that are useful for their specific task. This research analyzes different perspectives on the possibilities of time series environmental data visualization and visual data analysis (VDA) for health purposes. With the proposed categorization, some efforts are made to find the best ways to visualize time series data that should be used by citizens and doctors in order to give recommendations for behavior by location and place of residence. The categorization should be used from both users and researchers to identify future tasks in VDA of time series data, especially when that data are related to human health.

Because time is an important data dimension, special methods are required to support proper analysis and visualization to explore trends, patterns, and relationships in different types of time-oriented data. The human perceptual system is very sophisticated and specially adapted for perceiving visual patterns. For this reason, visualization is a highly appropriate method of data analysis and has been used successfully for data analysis of time series. When it comes to their use by medical and health professionals, these techniques should be easy to use, providing a wide range of visual analysis capabilities and comparing them with the permitted values for the measured pollutants [1].

Because of these specific uses of time series data visualization for health purposes, in this paper, we propose a framework – a model that should help to increase the comprehensibility of visual time series data analyzes for environmental data. Today, these data are collected in huge amounts, on different servers, in different formats and code systems, and the need for their efficient and fast analysis requires the application of fast and efficient methods for preparation and visualization. Visual analysis systems aim to overcome this lack of diversity and dispersion of time series data by applying and combining interactive visualization and VDA techniques.

The paper is organized as follows. Second chapter considers related works connected with visualization of time series data and VDA. The third chapter focuses on the characteristics of time series data and their usability, with emphasis on the use of the chronic disease and their physicians, considering the possibility of creating frame for VDA of time series data. The forth section considers mechanisms that can act on public awareness to reduce air pollution and how they can be activated in the society. The fifth chapter presents a way to visually present data and assess the risk for chronic disease by location, by creation of VDA and connecting these data with their chronic conditions. In this part the tools previously described in the context of mechanisms for raising public awareness to protect the patients' health, are considered. The sixth chapter proposes a model for VDA of time series for pollutants for the health purposes and patients (citizens) protection and validates the model with a practical example of a pollutant. The last chapter draws conclusions and proposes ways to capitalize the proposed model in the society as one of the mechanisms for public pressure to reduce pollution that should positively affect the improvement of environmental parameters.

2. Related works

For a long period, the time has been an interesting phenomenon that is studied by scientists, many times along with the location of the event that has been analyzed. A useful concept for data and information modeling, used in conjunction with cognitive principles, is the pyramidal framework, which is based on 3 perspectives: "where", "when" and "what" about data [2]. Interpretations form objects at a cognitively higher level of knowledge, classification, and interrelationships, taking into account both discrete and continuous phenomena. The most influential theories in the natural sciences are Newton's concepts of absolute and relative time. When modeling the time in information systems, the goal is not time itself, but to provide model that is most appropriate to represent the parameters under consideration of VDA. The time scale, scope, structure and views from different perspectives and the granularity of the data should be considered [2]. Techniques for VDA of time series take into account the following criteria: time together with its primitives, the level of abstraction and variability of data and their representation according to dimensionality and multivariate [3, 4]. Many tools have been created for this purpose.

Some well-known visualization techniques that represent time-oriented data consider time points. Such tools and techniques have a specific representation of time, on a time axis. For example, TimeWheel is a multi-axis representation for visualizing multiple variables over time and place a time axis in the center of the screen that can be rotated to bring different attributes into focus, zoom and move across the time axis. Because it uses lines to represent data for each time point, it is only useful for multiple variables related to time points but not to intervals [5].

A technique suitable for time intervals visualization and a high level of detail is PlanningLines, which consists of two encapsulated strips that represent the minimum and maximum duration, limited by two caps that represent the start and end intervals. This technique also solves the problem of time uncertainty related to future planning or different time granularities (as days or hours). This technique also supports interactive zooming and brushing, which is especially useful for fine-grained and large time scale [6].

An example of a tool that uses a time-point visualization technique is ThemeRiver, which represents the number of appearances on certain topics, for example, in print media, where each topic is displayed as a colored stream that changes its width continuously, such as flows through time [7, 8]. It is suitable for presenting quantitative data in time, but it is not suitable for presenting branching time or time with multiple perspectives or multivariate data. Because of this, the need for advanced techniques for effective visualization of multivariate data has been recognized.

If trends and patterns derived from multiple scales and univariate time series have to be visualized, it is appropriate to use cluster and calendar-based visualizations and data sets where colors are used to show data similarities [9]. Appropriate distance or similarity measures using data mining techniques provide cluster visualization and set the basis for clustering, neglecting the time context in a certain granularity, which complicates VDA in relation to basic time-oriented tasks [10].

Several researchers have worked on event-based visualization. Event specification is a step in which users describe their interests to find a match with the technique used and should therefore be based on formal descriptions and formulas of events. Such formulas contain elements of logic, variables, functions, aggregate functions, logical operators, and quantifiers that create valid formulas for events [11]. For time-oriented data analysis, it is necessary to have a sequence of types of events that are supported. For this purpose, a user-centric event specification model has been created that includes direct specification, parameterization and selection and provides expert and experiential visualization for users [11, 12].

When big data time series have to be visualized, many researchers use data mining methods to make different types of time data groupings [13]. Apart from the mentioned time tasks for data mining, other analytical methods are used as statistically combined operators [14] and extensions of the analysis of the main components [15].

There are many efforts to visualize time series with pixels. In this case, time can be represented using other visual variables if there is a mapping of time → space. If there is mapping time → time, the physical dimension time is used to convey the temporal dependence of the data through animations. The difference between these mappings is crucial for VDA, as different tasks and objectives are supported. There are also some hybrid forms, which combine the both mappings, as well as the data characteristics [12, 16]. Interaction and navigation methods are needed for data exploration as well as for parameter space exploration. In addition, it is important that these methods be designed according to certain requirements [17].

Direct interaction in the visual representation of the analytics methods, combined with the data mining methods provide greater control and better feedback to the analyst. This includes interactive parameterization of visual and analytical methods. The methods intended for navigation through large big data space are crucial for analyzing research-supporting environments. The tasks and goals of the user determine the choice of visualization method. If cycles in data should be identified, techniques that enable visual detection of periodic behavior need to be selected. In this case, techniques for visualizing time-oriented spiral data that have the ability to interact and animate in order to detect previously unknown cycles in the data can be appropriate [18].

Many practical examples of visualization and interaction methods show the requirements for the user to assess the limitations of the specific domain for the problem and therefore to choose the appropriate technique and tool for specific visualization and interaction components [5]. The idea of a time browser implemented in the TimeSearcher tool for exploring multiple time series can also be mentioned here [19]. Its purpose is to identify and find known data exploration models with user-defined search tolerance of a model that can allow varying degrees of accuracy and matching.

Exploratory data analysis (EDA) is also one of the rising areas in the recent decades, which is actually a return to the first goals of statistics, discovering and describing patterns, trends and relationships in data. It is more about generating hypotheses and less about hypothesis testing. Although not a strictly visual method, EDA is strongly associated with the usage of visual data representations [20]. Visual representations developed in EDA often are complemented by validation techniques, displaying vast data sets, multiple variables, temporally or spatially visualized with EDA visual data analysis. There are many useful and innovative techniques developed in visualization's tools for EDA purposes that include GIS and time-dependent mapping visualizations. These dynamic features include animation and interaction. Many of the EDA tasks use methods to research complex numerical data. Some analog techniques are developed in innovative ways to interact and explore abstract or non-numerical data that belong to the information visualization [21].

Information Visualization (InfoVis) deals with the mapping of abstract data that has led to new and important research on use and interaction of graphical representation space to display complex information efficiently and clearly [22]. Many combinations of GIS, EDA, and tool-assisted temporal visual techniques have been made with this concept in terms of using complex geo-spatial and temporal data in practice over the last three decades, as well as tools that support these complex visualizations [17, 18, 19, 21, 22, 23, 24, 25, 26].

3. Time series data and their characteristics

Time-oriented data visualization is not an easy task, although many approaches to this task have been published in the last years. The reason why most of the visualization methods are customized is simple: it is enormously difficult to consider all the aspects involved when visualizing time-oriented data. Time itself has many theoretical and practical aspects, whether working with time as a point on a time axis or time intervals using different sets of time relationships. Time is therefore interpreted as a linearly ordered set of time primitives, or it can be assumed that time primitives repeat cyclically. Time-bound data is another concern as it can be multiple, diverse, abstract, spatially referenced, or event-related. Therefore, it is necessary to think carefully when choosing visual techniques and tools for their analysis. If only the characteristics of the data are considered, it is possible to generate expressive visual representations, but usually visual representation requires thinking about the representative and perceptual issues of time series data, especially if they are related to environmental data [15].

Time series are simply measurements of tracked events' parameters, sampled, collected in different ways at specific time intervals [2, 17]. The difference between these time series data and other data sets is that they are always related to the time of occurrence and questions that can be asked are about changes over time. A simple way to determine if the database we are working with is a time series or not is to see if one of the axes, or one of the parameters is time or time period.

3.1. Concept of designing frames for time series visual data analysis

By proposing a concept for the development of visual data analysis frameworks for the time series of environmental data analysis, a vision of how the visual analysis of this data can be created and the necessary steps can be obtained as well as its components and functionality can be considered. It should not be a specific framework, but should describe the general steps and functionality of the main components involved. Individual components can be integrated into various specific applications in order to create a visual analytical framework or time-oriented data visualization system. For this purpose, it is necessary to firstly model the time-oriented environmental data, perform their computer analysis and make a display in interactive visualization.

Time series data come in two forms: regular and irregular [27]. The regular time series consist of measurements collected by software or hardware sensors at regular intervals (e.g., 10 seconds) and are often referred to as metrics. Irregular time series are event driven. Irregular time series sums can be seen as regular time series. For example, the average response time in the application, over an interval of one day, or the display of the average value of pollution per hour during the day are already regular time series. When they are in place of mechanisms to increase the public awareness of the citizens in a country, they are important information, especially if they affect human health [1, 28, 29].

4. Action mechanisms for public awareness to reduce pollution and how to activate them

Environmental reporting through indicators is an ambitious endeavor that should produce a report, a picture of the environment's state, presented with quantitative and qualitative data obtained through scientifically based measurements and analyzes. They should point to the sources, causes, consequences and trends of specific conditions. The prepared environmental indicators are based on numerical data showing the condition, special feature or movement of a certain phenomenon. Indicators can warn about problems and are a useful tool in the environmental reporting process. These indicators answer the key questions for the development of a country's environmental policy. The indicator is an inevitable tool for monitoring the achievement of sectoral policy objectives – strategies, plans, other documents and the basis for planning an effective policy for environmental protection and sustainable development [1].

All indicators from the environmental data set are arranged according to the framework known by the acronym DPSIR (Moving Forces – Pressures – Condition – Implications – Reactions) [1] where each phase conveys its meaning and importance and is clear about creating environmental protection policy. The driving forces are social and economic factors and activities that cause an increase or decrease in environmental pressures. They include economic, transport, social and other activities that affect the environment. Pressures are actually direct anthropogenic pressures and implications for the environment, such as emissions of pollutants or depletion of natural resources. Implications are the effects that environmental changes have on the human's health. Reactions are society's responses to environmental problems. These may include special measures of the state, such as taxes on the consumption of natural resources and penal provisions of the Law on environmental protection. Our goal will be to provide analysis of time series environmental data from accurate and geo-referenced measured values of the parameters that speak for the environment and to initiate the mechanism of

Implications – Reactions that should result in providing a better environment for citizens in the region following the indicators:

A – Descriptive indicator (gives an answer to the question "What is happening to the environment and people?", i.e. describes the current situation)

B – Progress indicator (gives an answer to the question "What is the distance between the existing situation and the established goal?", i.e. it compares the existing state of the environment with the established goals for environmental protection and serves to monitor the progress towards such goals)

C – Indicator for the efficiency of environmental protection (gives an answer to the question "Is the quality of the environment improving?", i.e. describes whether the society improves the quality of its products and processes in terms of resources, emissions and waste per unit of product)

D – Indicator of the effectiveness of the policy (gives an answer to the question "How effectively is the official policy of the country for the protection of the environment implemented?", i.e. whether and to what extent the official policy of the country is implemented)

E – Indicator for the overall well-being (gives an answer to the question "Has our situation completely improved?", i.e. describes whether and to what extent the country achieves sustainable development or economic development that ensures social welfare of citizens and environmental protection).

In order to detect these conditions on the indicators, visual data analysis for data of the north-western region of Republic of North Macedonia was performed and the data on the quality condition of the environmental parameters in the region were analyzed.

5. Assessment of the risk by patient's chronic disease by location

The analysis of the time series of the data for exposure of living organisms, and especially of humans, requires the generation of a comprehensive spatial-temporal record of exposure, obtained by recording the data obtained from the measurement sensors of environmental parameters [24, 29, 30]. The metadata they contain should describe the data, clarify the limits' values for all parameters and provide information related to the large amount of data that are collected and available in time series databases. The important platform's architecture is described, if the purpose is to integrate the diverse data that can be in the form of big data and obtained from sensors for measuring human health parameters.

Understanding the effects of modern human exposure to the environment and their impact on human health is an important domain in biomedical research [31]. Air pollution is associated with one of the eight leading causes of death globally and is associated with the emergence of many chronic diseases such as childhood asthma [28]. Although the contributions of these factors may vary, various studies show that at least 50% of human health problems are caused by environmental pollution, a person's lifestyle, and society's attitudes toward the environment. The phenomenon of the "individual" is the result of an interaction between his genome and the exosome, which is defined as "the total exposure of an individual throughout his life in the environment" [28, 29]. The assessment of the health risk from these pollutants for each individual can be done if we have data for parameters as pollution of the locations where they reside and his chronic health condition to which the parameters of the environment affect. This is also a complex and ambitious task involving an interdisciplinary approach that includes medical staff (for quantification of the impact of each exposure on each patient's disease code [24], patient health record data [32], ICD10 classification) as well as data scientists. The data scientists should create an assessment of the factors of environmental impact on the individual using healthcare big data analytics [33]. These data can be seen as the base for utilizing an application with methods and algorithms of artificial intelligence to assess the risk according to predefined parameters or rules.

Exposure can be estimated from the sensors' data for pollutants, with different parameters and accuracy, measured by different methods (as air pollution with PM10 particles, CO2, CO, N2, etc.). For this purpose, in many locations around the world, centers for measuring these parameters have been set up, because all countries are obliged to measure them and inform their citizens transparently. For example, the Center for Excellence in Health Informatics at Exposure (CEEHI) was established with funding from the National Institute of Biomedical Imaging and Children's Bioengineering Research, which uses integrated sensors [31]. The monitoring systems program has developed an infrastructure to support sensors based on weather data research [1].

5.1. Visualization of time series data for the specific locations

For the purpose of this paper, a visual data analysis of the time series data of pollutants were made for the cities of Tetovo, Gostivar and Kicevo with PM10 particles as well as in parts in Skopje municipality where sensors for measuring environmental parameters are present. By displaying the data in Power BI tool, users can easily analyze the days when the maximal permitted values for pollutants are exceeding and alarm patients with chronic diseases to avoid those locations where the value is higher than the maximum allowed, as shown in Figures 1, 2, 3. Although there are many applications that provide similar data, there is no organized effort to compare these data visually in the current time. However, by displaying visually and transparently these data and setting up locations that are polluted more than the limit of permitted values, it can be expected that this information will be used by patients, doctors and citizens to detect areas of pollution that exceed the permissible limits. This visual analysis can have a slider in order to be more flexible and allow to set up new limits of the permitted values for some chronic and more sensitive patients to these pollutions and thus to protect this population who have diagnoses on which these pollutants can have a devastating effect.

Other possibility is to list the diagnoses according to the ICD10 classification [33] and to indicate by the doctors which diseases are associated with certain pollutions, i.e., which of the pollutants can be fatal for patients with this chronic disease, how pollutants and their parameter's limit affect patients [24]. Some alerts through media can be published in order to protect the endangered citizen groups, to activate the mechanisms Implication – Reaction [1] and to influence the reactions to reduce pollutants. This also envisages recommendations to the chronic disease patients by medical staff to change temporarily the location of residence while a danger from particular pollutants lasts. All of these proposals require broader cooperation with the health sector and municipal and state institutions that can respond in the event of excessive pollutant values. Many examples of visualization in various visual forms can be created to be accessible and transparent, as well as predictions can be made for seasonal exceedances of pollutants such as PM10, PM2.5, CO, CO2, SO2, ozone and other pollutants that disrupt human health and destroy the ecosystem.

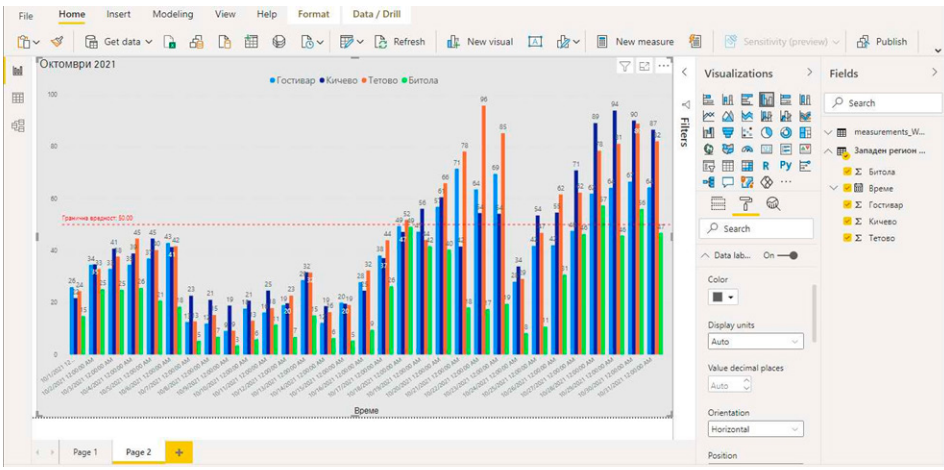

Figure 1: Visual analysis of pollution with PM10 particles for the month of October with a permitted value presented on the Clustered column chart [Gostivar – light blue, Kicevo – dark blue, Tetovo – brown and Bitola – green]

Figure 1 shows a visual data analysis of measured data for a dynamic period chosen by slider, on which the limit for the permitted value of the pollutant is shown. It can be seen that, on certain days, in some of the three cities, this value is exceeded. If the data are taken in real time, visualized with interactive VDA, the resulting visualizations can alert the patients with chronic diseases to distance themselves from these locations or temporarily leave these sites in order to protect their health.

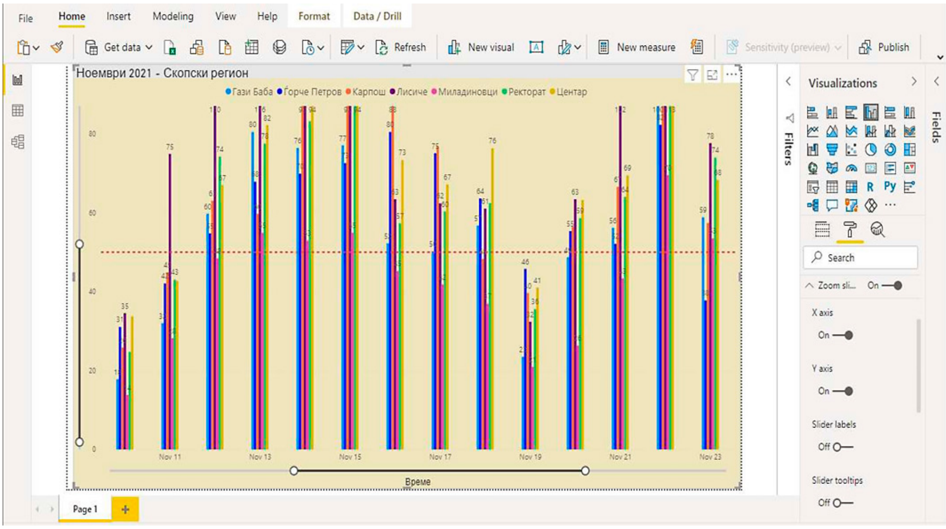

Figure 2: Usage of sliders along the X and Y axis for data from November 2021 for the Skopje region [Gazi Baba – light blue, Gjorce Petrov – Dark blue, Karpos – orange, Lisice – purple, Miladinovci – pink, Rectorate – green, Center – yellow. Limit value – horizontally dashed red line]

In addition, it can detect pollutants in time and therefore alert the responsible persons to take actions according the REACTION indicator [1].

The next example of VDA shown in Figure 2 provides a comparative analysis of PM10 particles pollution by regions in Skopje with a limit of permitted value for pollution. Figure 3 shows a line diagram for regional pollution, and each region is represented with a line in different color. Figure 4 displays VDA for 3 consecutive months on the Dashboard, enriched with slider and pollutant permitted limit that can be moved for the patients with chronic diseases. The permissible pollution limit for the given parameter is set on the visual display and shows excessive pollution that should trigger the mechanism REACTION of the Ministry of Environment Protection and INTERVENTION of the relevant authorities.

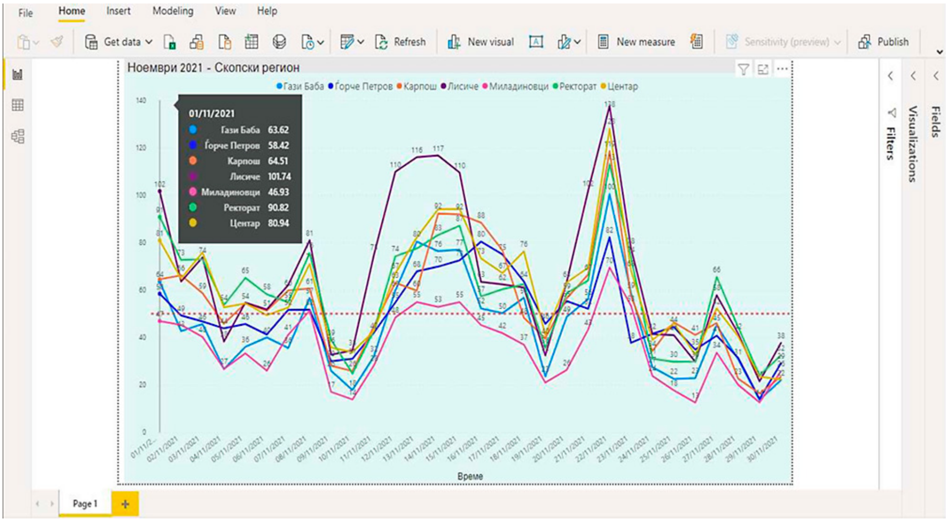

Figure 3: Visual data analysis of the PM10 pollutant for daily time series – Line chart [November 2021 – Skopje region]

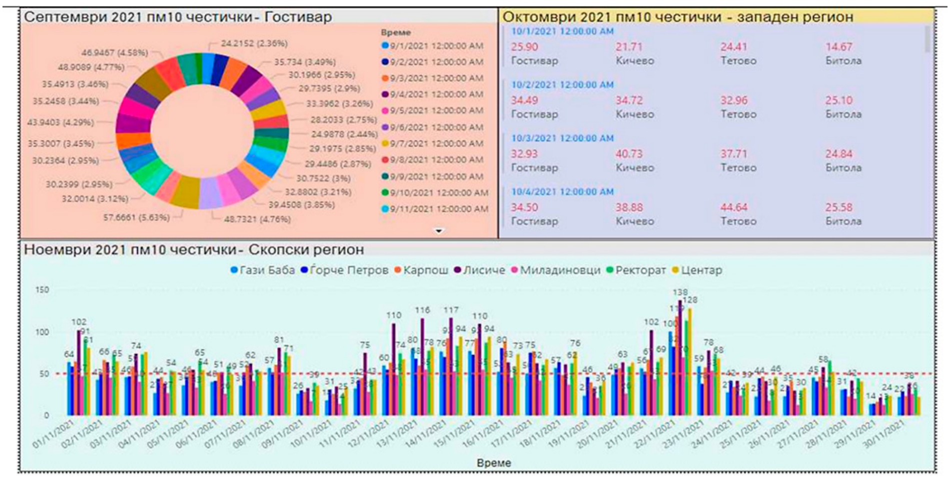

Figure 4: VDA of 3 consecutive months on the Dashboard with slider and permitted limit for PM10 made for proposed model validation

These images are understandable to users due to their comparability with the reference values that have to be respected and not be exceeded. It can serve as an easy way to provide information about the days (maybe time) when the permitted limits for the pollutants have been exceeded and to react.

6. Proposed model for VDA of time series data for pollutants intended for healthcare staff and patients

The experience gained by creating a large number of visualizations of environmental data from time series was used to extract a model – a framework for VDA of this type of data that includes the use of mobile applications that show air pollution by locations and citizens who have their own PHRs and diagnoses according to ICD10 classification of diseases [24]. Using environmental time series databases and defined pollutant values for the population and for each chronic obstructive pulmonary disease, each patient adjusts their permissible pollution limits according to their ICD10 diagnosis by PHR [32]. According to the pollutant that is analyzed, for each patient, a health risk assessment can be made and furthermore recommendations can be given by the system according to the principle of an expert system for diagnosis of chronic patients based on the IC10 classification, previously defined by specialist doctors [32, 33]. The model includes steps from event specification, pollutant types, and pollutant data loading, permitted limit of values and visual analysis appropriate to the representation, as well as possibilities for setting a filter and warning by the system. The proposed model is shown in Figure 5.

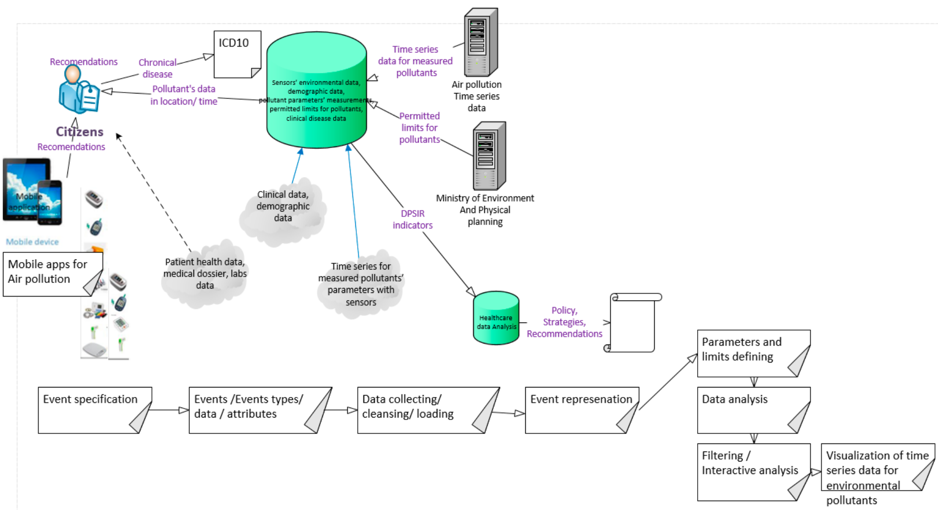

Figure 5: Proposed model of visual data analysis of environmental time series data for pollutants and their influence on the human health

The model assumes that the citizens (patients) are aware of their chronic condition and use a mobile application that can use the data obtained from servers that collect data on pollutants by time and location, their allowable limits, other sensors included in the data network and laboratory and other measurements available. They can also use mobile devices to measure their vital signs life parameters, connected to a mobile application for that purpose. The model assumes that the patient has digital health literacy and a culture of self-management of their health [32].

The second part of the model is intended for the creators of Policies and strategies at the municipal and regional level who through the mechanisms IMPLICATION – REACTION should react and prevent pollutants from causing such harmful consequences for human health. They should also apply the laws and penalties to sanction polluters and create recommendations for future actions of environmental policy makers [1].

The model assumes first to define the events (pollutants) that will be subject to data collection from time series, to make their detailed specification. Metadata structures are then created for intended events to collect and store data. The next phase is connected with the process of data collection, their clarification and refinement for storing in databases suitable for time series.

We validate the usability of the proposed model on many VDA for environmental pollutants, from different data sources of pollutants stored in time series, in different formats, and with different visualization techniques and tools, as shown in Figure 4.

We have to mention that there is possibility of using sensors to measure vital signs of life related to the user's mobile applications and their connection to pollutants' data, known as exposome.

7. Conclusion

The air pollution is a serious risk for citizens and public health everywhere. Therefore, it is necessary to strengthen the capacities for air quality management, especially in the part of preparation and monitoring the air quality of the national and local level with the plans' improvement. This presupposes the provision of accurate data, obtained from the air quality monitoring system in more locations and the creation of information from air data quality and their public presentation.

For this purpose, VDA are created and model for VDA from environmental data time series is proposed. This model can be used as a framework for visualization of this type of data applicable in similar situations. With the proposed model, pollutants' parameters limits can be shown on the screens for different groups of citizens with chronic diseases (as ICD10 codes from PHR), they can be alerted to avoid such locations and furthermore environmental authorities can be alerted to prevent these exceeding of the pollution's limits.

The model applicability is validated with creation of VDA dashboard for PM10 particle pollution from 3 months' data in time series of measured environmental data, using visualization according to the user's preferences that can be changed, made with Power BI. There is also the possibility of using sensors to measure vital signs of life related to the user's mobile applications and their connection to pollutants' data, also known as exposome. These data can provide the ability to assess the health risk of each citizen for their diagnosis [32], at that location at time [24], which can be one of the future research goals.

As opportunities for interesting visual insights from VDA can be mentioned the possibility provided by Power BI [34] for prediction of measured parameters that can be created according to data from previous years, seasonal trends and trend analysis. In addition, Accuweather [35] weather services can be included as the weather factor for prediction. This prediction can be made using visualizations in the Analytics section, where Forecast should be selected. This opportunity would provide forecasts for pollutants based on weather conditions and data about air pollution from previous years, which would be useful for the patients with chronic diseases to make suitable decisions in time, receiving alerts from the system and recommendations from their doctors. One of the future research topics that demands serious research using health big data analytics [33].

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