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PHD THESIS

INFORMATION TECHNOLOGY OF THE ENVIRONMENTAL POLLUTION MONITORING BASED ON TREND FORECASTING MODELS

126 Information Systems and Technologies
12 Information Technology

Applying for the Doctor of Philosophy degree

The PhD Thesis contains the results of own research. The use of ideas, results and texts of other authors are linked to the corresponding source

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SUMMARY

He Yuanfang. Information technology of the environmental pollution monitoring based on trend forecasting models. – *Qualifying scientific work as a manuscript.*

Thesis for the Doctor of Philosophy Degree in Specialty 126 «Information Systems and Technologies». – Taras Shevchenko National University of Kyiv, Kyiv, 2024.

Abstract. The dissertation is devoted to developing methods, models and information technology for monitoring the state of environmental pollution based on trend forecasting models, statistical fractal estimation, etc. The developed methods, models and information technology can be used to improve the efficiency of environmental management in the region, in particular in large cities, based on monitoring the level of pollution, the stability of pollution in the dynamics, the cyclicality of emissions, forecasting pollution levels for future periods and trends in future pollution levels.

Developing models of methods and information technology for monitoring environmental pollution is urgent. First, creating effective technologies for monitoring pollution is key to preserving citizens' health and quality of life, particularly in large cities. Monitoring the level of pollution and developing effective control strategies are critical to preserving the health of citizens. Effective pollution monitoring systems can also lead to economic benefits, including reduced disease treatment costs, improved quality of life, and promoting sustainable development. some types of pollution, such as greenhouse gas emissions, can lead to climate change, which has global impacts on ecosystems and human society. Monitoring and reducing these emissions is important to preserve the climate and reduce its negative impacts. Many countries have legislation regulating the level of environmental pollution. Developing and implementing effective monitoring systems helps ensure compliance with these regulations and standards.

In these conditions, several unresolved issues arise. There are no sufficiently developed systems that would be focused not only on measuring the level of

pollution by various indicators but also on making a qualitative forecast and assessing the state of the environment in a particular area. The structure of the time series of environmental pollution parameters can be a valuable source of information on the stability of pollution in the dynamics, the cyclical nature of harmful emissions, and helps to effectively predict pollution levels for future periods and trends in future pollution levels. Thus, the creation of methods, models and information technology for monitoring the state of environmental pollution based on trend forecasting models and statistical fractal estimation will practically improve the efficiency of environmental safety management and ensure a higher quality of life for citizens. The results obtained in this paper expand the theoretical and practical developments in this area.

Thus, this thesis solves an important task, namely, methods, models and information technology for monitoring the state of environmental pollution based on trend forecasting models, statistical fractal analysis, etc. The developed methods and models are practically integrated into the relevant monitoring information technology.

The object of research is the processes associated with monitoring and forecasting environmental pollution parameters for environmental safety management.

The subject of the study is methods, models and information technology for monitoring environmental pollution parameters based on trend forecasting models.

Research methods. The research is based on methods of knowledge representation and processing, monitoring and evaluation methods, time series forecasting methods, and statistical fractal analysis of information system design methods.

The study aims to develop methods, models, and information technology for monitoring environmental pollution parameters for environmental safety management.

Scientific novelty of the results:

- For the first time, a method of monitoring environmental pollution parameters based on a comprehensive model for predicting time series of pollution parameters for decision-making on environmental safety management is described.
- The model for predicting time series of environmental pollution is improved, considering the aggregation of various prediction models formed based on a predictive statistical analysis of pollution indicators. The model differs from the known models by providing the ability to adapt the model parameters to changes in the state of the environment, which is especially important when using such models in environmental monitoring systems.
- An improved model for assessing the state of the environment in the monitoring system, which, unlike the known ones, takes into account the results of comprehensive forecasting of time series of changes in pollution and can be a tool for ensuring environmental safety.
- The information technology for monitoring environmental pollution parameters was improved, which is distinguished by taking into account the results of analysis and forecasting of changes in pollution parameters and offers an assessment of the state of the environment, which provides opportunities for quantitative assessment of the environmental situation in the region.
- The direction of developing an environmental index based on the developed methods of monitoring and forecasting time series of pollution and characterized by the consideration of prospective pollution indicators, which can be used in urban environmental monitoring and conditions of environmental uncertainty, was further developed.

The first section describes the basic concepts and features of environmental monitoring. The necessity to increase the efficiency of monitoring and the main approaches to their solution through the improvement of methods and technologies are substantiated. The analysis of the properties of time series of pollutants shows that they can be classified into three classes: substances with a pronounced seasonal component, substances with a pronounced trend, and random variables. Such a classification allows for a better selection of forecasting and data transformation methods that can be used more effectively for each class of substances.

The problem of environmental monitoring has been formalized in two formulations: point and plane. The main stages of environmental monitoring are highlighted. These are collecting data on the history of the state, monitoring the current state and predicting the state of environmental pollution in the future. Approaches and requirements for technical means at each stage are proposed. A review of known systems for monitoring air, water and soil pollution is made. The importance of the technical component is shown. Fundamental differences and new trends in the use of innovative technologies for monitoring environmental pollution parameters are identified.

A scientific hypothesis defines the author's vision of an environmental monitoring organization by combining software and hardware systems and using trend models to predict environmental pollution parameters. By formalizing the problem of environmental monitoring, the structure of the information system for environmental monitoring is proposed. The information system should include the following subsystems: a subsystem for collecting information about the state of the environment, a subsystem for storing and accumulating data, forecasting the state of the environment, and a subsystem for user interaction. It is indicated that constructing an air pollution monitoring system is also essential for the whole and safe operation of some critical infrastructure facilities, including power plants, processing and chemical plants, airports, tunnels and subways, etc.

The second section describes a comprehensive model for forecasting time series of environmental pollution indicators, considering the aggregation of various forecasting models formed based on a predictive statistical analysis of pollution indicators and having an adaptive nature. The model differs from the known models by providing the ability to adapt the model parameters to changes in the state of the environment, which is especially important when using such models in environmental monitoring systems. The fractal analysis method of time series is described, which allows finding the Hurst index for use in the developed forecasting models and determining the presence of long-term memory, cyclicity, etc., in the time series.

The complex forecasting model includes higher-order exponential smoothing, Holt, Winters, moving average, weighted moving average, and autoregressive models. All the parameters set in these models are related to the Hurst index, which is calculated based on the predictive fractal statistical analysis of the time series. The corresponding descriptions and justifications are given. Using such a model as part of an econometric system will help to more effectively predict and respond to possible changes in the values of pollution parameters. In particular, the persistence of the time series of pollution parameters may mean a stable upward or downward trend in pollution. Suppose the time series becomes close to random or ergodic. In that case, this may mean an emergency or that additional non-permanent emissions have appeared in the region that need to be monitored.

The third section describes a method for monitoring environmental pollution parameters based on a comprehensive model for predicting time series of pollution parameters with the use of statistical fractal analysis. The method takes into account the results of statistical fractal analysis to determine the direction of the time series trend, which may indicate whether the amount of pollution is increasing or decreasing in the short term. The method also determines the average cycle length based on the V statistic, which establishes the presence of long-term memory in the time series and determines the reliability of the trend forecast calculation.

In addition, the Hurst index determines whether emissions of harmful substances, particularly into the air, are stable. That is, it is shown that if the Hurst index of a time series indicates that the time series is close to random, the environmental situation in the area is unstable, and excessive emissions are possible. This means local governments and environmental services should respond to this situation to ensure environmental safety. The model for assessing the state of the environment in the monitoring system has been improved, which, unlike the known ones, takes into account the results of comprehensive forecasting of time series of pollution changes and can be a tool for ensuring environmental safety. The model establishes a comprehensive assessment of the state of the environment based on the method of monitoring environmental pollution parameters. The direction of developing an index of the state of the environment, based on the developed methods of monitoring and forecasting time series of pollution and characterized by the consideration of prospective pollution indicators, which can be used in urban environmental monitoring and conditions of environmental uncertainty, has been further developed.

The fourth section describes the information technology for monitoring environmental pollution parameters, which is distinguished by taking into account the results of analysis and forecasting changes in pollution parameters and offers an assessment of the state of the environment, which provides opportunities for quantitative assessment of the environmental situation in the region. Information technology includes methods for collecting information, a method for monitoring environmental pollution parameters, a model for assessing the state of the environment in the monitoring system, a method for calculating the environmental condition index, time series forecasting models, a method for statistical fractal analysis of time series, etc. All of these components allow for a qualitative analysis of the region's environmental situation and predict its future change.

The information technology for monitoring pollution parameters based on a monitoring method that uses a comprehensive forecasting model, time series trend prediction, and statistical fractal analysis was verified. The verification was carried out on the example of a time series of environmental pollution parameters in different districts of Beijing, which were recorded from 2013 to 2017. The calculated errors in forecasting and assessing the state of the environment show the effectiveness of the development of such information technology and the relevance of this development for use by the city's environmental services and government agencies. Acts on implementing the results of work within the framework of research projects of Yancheng Polytechnic College (Appendix A).

The practical significance of the results obtained is that the developed methods, models, and information monitoring of environmental pollution parameters will improve the efficiency of managing the state's environmental state. The resulting tool is important practically for ecological services and public authorities. In the long term, using the developed methods and models will positively impact the development of environmental policy in the state. The main provisions and results of the research were implemented and applied in the activities of Yancheng Polytechnic College.

The results obtained, both in theoretical and practical terms, serve as a basis for further scientific and applied research to improve and enhance various aspects of the state's environmental management.

Keywords: information technology, environmental monitoring, forecasting model, mathematical model, project management, time series, decision-making, evaluation task, fractal analysis, information management, critical infrastructure, environmental safety.

LIST OF PUBLICATIONS OF THE APPLICANT BY PHD THESIS TOPIC

Articles in professional publications of Ukraine

(included in the list of the Ministry of Education and Science of Ukraine)

1. **Yuanfang, He, & Vatskel, Igor,** (2019). Problem of evaluation of pollution of the environment. Management of development of complex systems, 37, 168 – 172. [category «B»] https://doi.org/10.6084/m9.figshare.9783230 https://urss.knuba.edu.ua/files/zbirnyk-37/29.pdf

2. **Yuanfang, He,** (2019). Fomalization of the problem of evaluation of pollution of the environment. Management of development of complex systems, 38, 168 – 172. [category «B»] https://doi.org/10.6084/m9.figshare.9788702 https://urss.knuba.edu.ua/files/zbirnyk-38/28.pdf

3. **He, Y., & Biloshchytskyi, A. O.** (2019). Hardware of the information system for environmental pollution monitoring. Scientific Bulletin of Uzhhorod University. Series of Mathematics and Informatics, 2(35), 143–148. [category «B»] https://doi.org/10.24144/2616-7700.2019.2(35).143-148 http://visnyk-math.uzhnu.edu.ua/article/view/189498/188916

4. **Yuanfang, He** (2024). Development of a trend forecasting model for environmental pollution monitoring. Management of development of complex systems, 57, 62 – 66. [category «B»] https://doi.org/10.32347/2412-9933.2024.57.62-66

Articles in professional publications of Ukraine

(not included in the list of the Ministry of Education and Science of Ukraine)

1. **Yuanfang, He.** (2020). Formation of requirements for the information system of environmental monitoring. *Science Journal Innovation Technologies Transfer*. 56-60. https://doi.org/10.36381/iamsti.4.2020.56-60

Approbation works

1. **He, Y., Kuchansky, A., Paliy, S. & Shabala, Y.** (2021). Problems in Air Quality Monitoring and Assessment, 2021 IEEE International Conference on Smart Information Systems and Technologies (SIST), Nur-Sultan, Kazakhstan, 1-4, https://doi.org/10.1109/SIST50301.2021.9465915 [**Scopus, Web of Science**]

2. **Yuanfang, He.** (2020). Developing requirements for the information system of environmental monitoring. Seventh international scientific-practical conference «Management of the development of technologies» Topic: "Information technology development of educational content» Kyiv, 25 – 26 March 2020, 129-130. [In Ukrainian]

3. **Yuanfang, He.** (2019). Concept of information system for monitoring environmental pollution. XV International Scientific and Practical Conference "Project Management in the Development of Society", May 17-18, 2019, 58-59

4. **Yuanfang, He.** (2019). Monitoring of pollution by analysis traffic on city roads. I International Scientific and Practical Conference IMTCK2019, 61-64.

5. **Yuanfang, He.** (2019). Participatory sensing for monitoring and forecasting of environmental pollution. VI International Scientific and Practical Conference "Information Technologies and Interactions", December 20, 2019, 95-96.

6. **Yuanfang, He.** (2018). Participatory sensing for monitoring and forecasting of environmental pollution. V International Scientific and Practical Conference "Information Technologies and Interactions", November 20-21, 2018, 52-53.

АНОТАЦІЯ

Хе Юаньфанг. Інформаційна технологія моніторингу забруднення навколишнього середовища на основі трендових моделей прогнозування – *Кваліфікаційна наукова праця на правах рукопису.*

Дисертація на здобуття наукового ступеня доктора філософії за спеціальністю 126 «Інформаційні системи та технології» – Київський національний університет імені Тараса Шевченка, Київ, 2024.

Зміст анотації. Дисертація присвячена побудові методів, моделей та інформаційної технології моніторингу стану забруднення навколишнього середовища на основі трендових моделей прогнозування, статистичного фрактального оцінювання тощо. Побудовані методи, моделі та інформаційна технологія може бути використана для підвищення ефективності управління екологічною ситуацією в регіоні, зокрема у великих містах, на основі моніторингу рівня забрудненості, стабільності забрудненості в динаміці, циклічності обсягів шкідливих викидів, прогнозування рівнів забруднення на майбутні періоди та трендів зміни рівнів забруднення в майбутньому.

Актуальність задачі розроблення моделей методів та інформаційної технології для моніторингу рівня забрудненості навколишнього середовища є актуальною. По-перше створення ефективних технологій для моніторингу забрудненості є запорукою збереження здоров’я горомадян та їх якісного життя, зокрема в умовах великих міст. Моніторинг рівня забрудненості та розробка ефективних стратегій контролю є критично важливими для збереження здоров'я громадян. Ефективні системи моніторингу забруднення також можуть призводити до економічних переваг, включаючи зменшення витрат на лікування захворювань, покращення якості життя та сприяння

сталому розвитку. еякі види забруднення, такі як викиди парникових газів, можуть призводити до змін клімату, що має глобальний вплив на екосистеми та людське суспільство. Моніторинг та зменшення цих викидів є важливим завданням для збереження клімату та зменшення його негативного впливу. Багато країн мають законодавство, що регулює рівень забрудненості навколишнього середовища. Розробка та впровадження ефективних систем моніторингу допомагає забезпечити відповідність цим нормам та стандартам.

В цих умовах виникає ряд невирішених питань, а саме: немає достатньо розроблених систем, які б були зорієнтовані не тільки на вимірювання рівня забрудненості по різним показникам, але і робили якісний прогноз та оцінку стану навколишнього середовища у визначеній місцевості. Структура часових рядів параметрів забруднення навколишнього середовща може бути цінним джерелом інформації про рівень стабільності забрудненості в динаміці, циклічності обсягів шкідливих викидів, домомагає ефективно прогнозувати рівні забруднення на майбутні періоди та тренди зміни рівнів забруднення в майбутньому. Таким чином створення методів, моделей та інформаційної технології моніторингу стану забруднення навколишнього середовища на основі трендових моделей прогнозування, статистичного фрактального оцінювання дозволить практично підвищити ефективність управління екологічною безпекою та забезпечити вищу якість життя громадян. Результати, які отримані в даній роботі розширяють теоретичні та практичні напрацювання в даному напрямку.

Отже, в даній дисертаційній роботі вирішується важливе завдання, а саме: методів, моделей та інформаційної технології моніторингу стану забруднення навколишнього середовища на основі трендових моделей прогнозування, статистичного фрактального аналізу тощо. Розроблені методи та моделі практично інтегруються у відповідній інформаційній технології моніторингу.

Об’єктом дослідження є процеси, які пов’язані з моніторингом та прогнозуванням параметрів забруднення навколишнього середовища для управління екологічною безпекою.

Предметом дослідження є методи, моделі та інформаційна технологія моніторингу параметрів забруднення зовнішнього середовища, які базуються на трендових моделях прогнозування.

Методи дослідження. Проведені дослідження базуються на методах представлення і обробки знань, методах моніторингу та оцінювання, методах прогнозування часових рядів, статистичного фрактального аналізу методів проєктування інформаційних систем.

Метою дослідження є розроблення методів, моделей та інформаційної технології моніторингу параметрів забруднення навколишнього середовища для управління екологічною безпекою.

Наукова новизна отриманих результатів:

- вперше описано метод моніторингу параметрів забруднення навколишнього середовища, що базується на основі комплексної моделі прогнозування часових рядів параметрів забруднення для прийняття рішень щодо управління екологічною безпекою.

- удосконалено модель прогнозування часових рядів забруднення навколишнього середовища з врахуванням агрегації різних моделей прогнозування, що формуються на основі передпрогнозного статистичного аналізу показників забруднення. Модель відрізняється від відомих моделей забезпеченням можливістю адаптації параметрів моделі до змін у стані навколишнього середовища, що особливо важлива в умовах використання таких моделей в системах екомоніторингу.

- удосконалено модель оцінювання стану навколишнього середовища в системі моніторингу, що навідміну від відомих, враховує результати комплексного прогнозування часових рядів зміни забрудненості і може бути інструментом забезпечення екологічної безпеки.

- удосконалено інформаційну технологію моніторингу параметрів забруднення навколишнього середовища, що відрізняється врахуванням результатів аналізу та прогнозування зміни параметрів забруднення та пропонує оцінку стану навколишнього середовища, що надає можливості кількісного оцінювання екологічної ситуації в регіоні.
- отримав подальший розвиток напрямок розроблення індексу стану зовнішнього середовища, що базується на розроблених методах моніторингу та прогнозування часових рядів забрудненості і відрізняється врахуванням проспективних показників забруднення, що може використовуватись в урбаністичному екомоніторингу та в умовах екологічної невизначеності.

У першому розділі описано основні поняття та особливості моніторингу стану навколишнього середовища. Обґрунтовано необхідність підвищення ефективності моніторингу, та основні підходи до їх вирішення шляхом удосконалення методів та технологій. Аналіз властивостей часових рядів забрудників показує що їх можна класифікувати на 3 класи: речовини з ярко вираженою сезонною складовою, речовини із вираженим трендом та випадкові величини. Така класифікація дає змогу краще підбирати методи прогнозування та перетворення даних які більш ефективно можна застосовувати для кожного із класів речовин.

Здійснено формалізацію задачі моніторингу стану навколишнього середовища в двох постановках: точковій і на площині. Виділено основні етапи моніторингу стану навколишнього середовища. Збір даних про історію стану, спостереження за поточним станом та прогнозування стану забруднення навколишнього середовища в майбутньому. Запропоновано підходи та необхідні вимоги щодо технічних засобів на кожному із етапів. Здійснено огляд відомих систем моніторингу стану забруднення повітря, води і грунтів. Показана важливість технічної складової. Виявлено принципові відмінності та нові тренди щодо застосування інноваційних технологій моніторингу параметрів забруднення навколишнього середовища.

Сформульована наукова гіпотеза яка визначає бачення автора щодо організації моніторингу стану навколишнього середовища з точки зору поєднання програмних і апаратних комплексів та застосування трендових моделей для прогнозування параметрів забрудження навколишнього середовища. Відповідно до цієї формалізації задачі моніторингу стану навколишнього середовища запропонована структура інформаційної системи моніторингу стану навколишнього середовища. Інформаційна система має включати такі підсистеми: підсистема збору інформації про стан навколишнього середовища, підсистема збереження та накопичення даних, прогнозування стану навколишнього середовища та підсистема взаємодії із користувачем. Зазначається, що побудова системи моніторингу забруднення повітря також необхідна для повноцінної та безпечної роботи деяких об'єктів критичної інфраструктури, включаючи електростанції, переробні та хімічні заводи, аеропорти, тунелі та метрополітени тощо.

В другому розділі описано комплексну модель прогнозування часових рядів показників забруднення навколишнього середовища з врахуванням агрегації різних моделей прогнозування, що формуються на основі передпрогнозного статистичного аналізу показників забруднення та має адаптивний характер. Модель відрізняється від відомих моделей забезпеченням можливістю адаптації параметрів моделі до змін у стані навколишнього середовища, що особливо важлива в умовах використання таких моделей в системах екомоніторингу. Описано метод фрактального аналізу часових рядів, який дозволяє знайти показник Херста для використання його в складі розроблених моделей прогнозування і дозволяє визначити наявність в часовому ряді довготрималої пам’яті, циклічності тощо.

В склад комплексної моделі прогнозування включено моделі експоненціального згладжування вищого порядку, моделі Хольта, Вінтерса, плинної середньої, зваженої плинної середньої, авторегресійної моделі. Всі параметри, які задаються в цих моделях пов’язані з показником Херста, який розраховується на основі передпрогнозного фрактального статистичного аналізу часового ряду. Наведені відповідні описання та обгрунтування. Вказано, що використання такої моделі в складі системи екомоніторингу допоможе ефективніше передбачати та реагувати на можливі зміни значень параметрів забруднення. Зокрема, персистентність часового ряду параметрів забруднення може означати стабільну тенденцію до зростання або спадання забруднення. Якщо ж часовий ряд стає близьким до випадкового або ергодичним, то це може означати надзвичайну ситуацію, або ж те, що в регіоні з'явилися додаткові непостійні викиди, які необхідно моніторити.

В третьому розділі описано метод моніторингу параметрів забруднення навколишнього середовища, що базується на основі комплексної моделі прогнозування часових рядів параметрів забруднення з врахуванням статистичного фрактального аналізу. Метод враховує результати статистичного фрактального аналізу для встановлення напрямку тренду часового ряд, що може вказувати на те чи зростає, чи спадає величина забруднення в короткостроковій перспективі. Також метод використовує метод визначення середньої довжини циклу на основі поубдови V статистики, що дозоляж встановити наявність довготривалої пам'яті у часового ряду та визначити надійність розрахунку прогнозу тренду. Крім того, на основі показника Херста визначається чи стабільними є викиди шкідливих речовин, зокрема в повітря. Тобто, показано, що якщо показник Херста часовго ряду вказує на те, що часовий ряд близький до випадкового, то це означає, що екологічна ситуація в районі є нестабільною, можливі понаднормові викиди. Це означає, що органи місцевого самоврядування та екологічні служби повинні реагувати на цю ситуацію для забезпечення екологічної безпеки. Удосконалено модель оцінювання стану навколишнього середовища в системі моніторингу, що на відміну від відомих, враховує результати комплексного прогнозування часових рядів зміни забрудненості і може бути інструментом забезпечення екологічної безпеки. Модель встановлює комплексну оцінку стану зовнішнього середовища на основі методу моніторингу параметрів забруднення навколишнього середовища. Отримав подальший розвиток напрямок розроблення індексу стану зовнішнього середовища, що базується на розроблених методах моніторингу та прогнозування часових рядів забрудненості і відрізняється врахуванням проспективних показників забруднення, що може використовуватись в урбаністичному екомоніторингу та в умовах екологічної невизначеності.

У четвертому розділі описано інформаційну технологію моніторингу параметрів забруднення навколишнього середовища, що відрізняється врахуванням результатів аналізу та прогнозування зміни параметрів забруднення та пропонує оцінку стану навколишнього середовища, що надає можливості кількісного оцінювання екологічної ситуації в регіоні. Інформаційна технологія включає методи збору інформації, метод моніторингу параметрів забруднення навколишнього середовища, модель оцінювання стану навколишнього середовища в системі моніторингу, метод розрахунку індексу стану зовнішнього середовища, моделі прогнозування часових рядів, метод статистичного фрактального аналізу часових рядів тощо. Всі ці складники дозволяють зробити якісний аналіз стану навколишнього середовища в регіоні та передбачити його зміну в майбутньому.

Верифіковано інформаційну технологію моніторингу параметрів забруднення на основі методу моніторингу, що використовує комплексну модель прогнозування, передбачення трендів часових рядів та статистичний фрактальний аналіз. Верифікація відбувалась на прикладі часових рядів параметрів забруднення навколишнього середовища в різних районах міста Пекін, що були зафіксовані з 2013 по 2017 роки. Розраховані прохибки прогнозування та оцінки стану навколишнього середовища показують ефективність розробки такої інформаційної технології, а також актуальності цієї розробки для використання екологічними службами міста та державними органами. Отримані акти про впровадження результатів роботи в межах науково-дослідних проєктів Yancheng Politecnic College (Додаток А).

Практичне значення одержаних результатів полягає у тому, що розроблені методи, моделі та інформаційна моніторингу параметрів забруднення навколишнього середовища дозволить підвищити ефективність управління екологічним станом держави. Отриманий інструмент є важливим практично для еологійних служб, органів державної влади. В довготривалій перспективі використання розроблених методів та моделей дасть позитивний вплив на розвиток екологічної політики в держави. The main provisions and results of the research were implemented and applied in the activities of Yancheng Polytecnic College.

Отримані результати, як у теоретичному, так і практичному плані, служать основою для подальших науково-прикладних досліджень, спрямованих на удосконалення та покращення різних аспектів управління екологічним станом держави.

Ключові слова: інформаційна технологія, екологічний моніторинг, модель прогнозування, математична модель, управління проєктами, часовий ряд, прийняття рішень, задача оцінювання, фрактальний аналіз, інформаційний менеджмент, критична інфраструктура, екологічна безпека.

СПИСОК ПУБЛІКАЦІЙ ЗДОБУВАЧА ЗА ТЕМОЮ ДИСЕРТАЦІЇ

Статті у фахових виданнях України

(входять до переліку МОН України)

1. **Yuanfang, He, & Vatskel, Igor,** (2019). Problem of evaluation of pollution of the environment. Management of development of complex systems, 37, 168 – 172. [category «B»] https://doi.org/10.6084/m9.figshare.9783230 https://urss.knuba.edu.ua/files/zbirnyk-37/29.pdf

2. **Yuanfang, He,** (2019). Fomalization of the problem of evaluation of pollution of the environment. Management of development of complex systems, 38, 168 – 172. [category «B»] https://doi.org/10.6084/m9.figshare.9788702 https://urss.knuba.edu.ua/files/zbirnyk-38/28.pdf

3. **He, Y., & Biloshchytskyi, A. O.** (2019). Hardware of the information system for environmental pollution monitoring. Scientific Bulletin of Uzhhorod

University. Series of Mathematics and Informatics, 2(35), 143–148. [category «B»] https://doi.org/10.24144/2616-7700.2019.2(35).143-148
http://visnyk-math.uzhnu.edu.ua/article/view/189498/188916

4. **Yuanfang, He** (2024). Development of a trend forecasting model for environmental pollution monitoring. Management of development of complex systems, 57, 62 – 66. [category «B»] https://doi.org/10.32347/2412-9933.2024.57.62-66

Статті у фахових виданнях України

(не входять до переліку МОН України)

1. **Yuanfang, He.** (2020). Formation of requirements for the information system of environmental monitoring. *Science Journal Innovation Technologies Transfer*. 56-60. https://doi.org/10.36381/iamsti.4.2020.56-60

Опубліковані праці апробаційного характеру

1. **He, Y., Kuchansky, A., Paliy, S. & Shabala, Y.** (2021). Problems in Air Quality Monitoring and Assessment, 2021 IEEE International Conference on Smart Information Systems and Technologies (SIST), Nur-Sultan, Kazakhstan, 1-4, https://doi.org/10.1109/SIST50301.2021.9465915 [**Scopus, Web of Science**]

2. **Yuanfang, He.** (2020). Developing requirements for the information system of environmental monitoring. Seventh international scientific-practical conference «Management of the development of technologies» Topic: "Information technology development of educational content» Kyiv, 25 – 26 March 2020, 129-130. [In Ukrainian]

3. **Yuanfang, He.** (2019). Concept of information system for monitoring environmental pollution. XV International Scientific and Practical Conference "Project Management in the Development of Society", May 17-18, 2019, 58-59

4. **Yuanfang, He.** (2019). Monitoring of pollution by analysis traffic on city roads. I International Scientific and Practical Conference IMTCK2019, 61-64.

5. **Yuanfang, He.** (2019). Participatory sensing for monitoring and forecasting of environmental pollution. VI International Scientific and Practical Conference "Information Technologies and Interactions", Dec. 20, 2019, 95-96.

6. **Yuanfang, He.** (2018). Participatory sensing for monitoring and forecasting of environmental pollution. V International Scientific and Practical Conference "Information Technologies and Interactions", November 20-21, 2018, 52-53.

CONTENT

INTRODUCTION

The dissertation is devoted to developing methods, models and information technology for monitoring the state of environmental pollution based on trend forecasting models, statistical fractal estimation, etc. The developed methods, models, and information technology can be used to improve the efficiency of environmental management in the region, in particular in large cities, based on monitoring the level of pollution, the stability of pollution in the dynamics, the cyclicality of emissions, forecasting pollution levels for future periods and trends in future pollution levels.

Developing models of methods and information technology for monitoring environmental pollution is urgent. First, creating effective technologies for monitoring pollution is key to preserving citizens' health and quality of life, particularly in large cities. Monitoring the level of pollution and developing effective control strategies are critical to preserving the health of citizens. Effective pollution monitoring systems can also lead to economic benefits, including reduced disease treatment costs, improved quality of life, and promoting sustainable development. some types of pollution, such as greenhouse gas emissions, can lead to climate change, which has global impacts on ecosystems and human society. Monitoring and reducing these emissions is important to preserve the climate and reduce its negative impacts. Many countries have legislation regulating the level of environmental pollution. Developing and implementing effective monitoring systems helps ensure compliance with these regulations and standards.

In these conditions, several unresolved issues arise. There needs to be sufficiently developed systems that would be focused not only on measuring the level of pollution by various indicators but also on making a qualitative forecast and assessment of the state of the environment in a particular area. The structure of the time series of environmental pollution parameters can be a valuable source of information on the stability of pollution in the dynamics and the cyclical nature of harmful emissions and helps to effectively predict pollution levels for future periods and trends in future pollution levels. Thus, the creation of methods, models and information technology for monitoring the state of environmental pollution based on trend forecasting models and statistical fractal estimation will improve the efficiency of environmental safety management and ensure a higher quality of life for citizens. The results obtained in this paper expand the theoretical and practical developments in this area.

Thus, this thesis solves an important task, namely, methods, models and information technology for monitoring the state of environmental pollution based on trend forecasting models, statistical fractal analysis, etc. The developed methods and models are practically integrated into the relevant monitoring information technology.

The dissertation work was carried out at the Faculty of Information Technologies of Taras Shevchenko National University of Kyiv following the plan of research works of Taras Shevchenko National University of Kyiv, in particular the topic "Information technologies of analysis and forecasting of processes, invariant to the subject area", No. 0123U101621.

The object of research is the processes associated with monitoring and forecasting environmental pollution parameters for environmental safety management.

The subject of the study is methods, models and information technology for monitoring environmental pollution parameters based on trend forecasting models.

Research methods. The research is based on methods of knowledge representation and processing, monitoring and evaluation methods, time series forecasting methods, and statistical fractal analysis of information system design methods.

The study aims to develop methods, models, and information technology for monitoring environmental pollution parameters for environmental safety management.

To achieve the goal, the following tasks must be solved:

1. Analyze the features and relevance of monitoring environmental pollution parameters and formalize this task.

2. To describe the model for predicting time series of environmental pollution, considering the aggregation of various prediction models formed based on statistical fractal analysis of pollution indicators.

3. Describe a method for monitoring environmental pollution parameters based on an integrated time series forecasting model and determine a model for assessing the state of the environment in the monitoring system and the environmental condition index based on the developed methods for monitoring and forecasting time series of pollution.

4. Describe an improved information technology for monitoring environmental pollution parameters, considering the results of analysis and forecasting changes in pollution parameters based on the developed models and methods.

Scientific novelty of the results:

- For the first time, a method of monitoring environmental pollution parameters based on a comprehensive model for predicting time series of pollution parameters for decision-making on environmental safety management is described.
- The model for predicting time series of environmental pollution is improved, considering the aggregation of various prediction models formed based on a predictive statistical analysis of pollution indicators. The model differs from the known models by providing the ability to adapt the model parameters to changes in the state of the environment, which is especially important when using such models in environmental monitoring systems.
- An improved model for assessing the state of the environment in the monitoring system, which, unlike the known ones, takes into account the results of comprehensive forecasting of time series of changes in pollution and can be a tool for ensuring environmental safety.

- The information technology for monitoring environmental pollution parameters was improved, which is distinguished by taking into account the results of analysis and forecasting of changes in pollution parameters and offers an assessment of the state of the environment, which provides opportunities for quantitative assessment of the environmental situation in the region.
- The direction of developing an environmental index based on the developed methods of monitoring and forecasting time series of pollution and characterized by the consideration of prospective pollution indicators, which can be used in urban environmental monitoring and conditions of environmental uncertainty, was further developed.

The first section describes the basic concepts and features of environmental monitoring. The necessity to increase the efficiency of monitoring and the main approaches to their solution through the improvement of methods and technologies are substantiated. The analysis of the properties of time series of pollutants shows that they can be classified into three classes: substances with a pronounced seasonal component, substances with a pronounced trend, and random variables. Such a classification allows for a better selection of forecasting and data transformation methods that can be used more effectively for each class of substances.

The problem of environmental monitoring has been formalized in two formulations: point and plane. The main stages of environmental monitoring are highlighted. These are collecting data on the history of the state, monitoring the current state and predicting the state of environmental pollution in the future. Approaches and requirements for technical means at each stage are proposed. A review of known systems for monitoring air, water and soil pollution is made. The importance of the technical component is shown. Fundamental differences and new trends in the use of innovative technologies for monitoring environmental pollution parameters are identified.

A scientific hypothesis defines the author's vision of an environmental monitoring organization by combining software and hardware systems and using trend models to predict environmental pollution parameters. By formalizing the problem of environmental monitoring, the structure of the information system for environmental monitoring is proposed. The information system should include the following subsystems: a subsystem for collecting information about the state of the environment, a subsystem for storing and accumulating data, forecasting the state of the environment, and a subsystem for user interaction. It is indicated that constructing an air pollution monitoring system is also essential for the whole and safe operation of some critical infrastructure facilities, including power plants, processing and chemical plants, airports, tunnels, and subways, etc.

The second section describes a comprehensive model for forecasting time series of environmental pollution indicators, considering the aggregation of various forecasting models formed based on a predictive statistical analysis of pollution indicators and having an adaptive nature. The model differs from the known models by providing the ability to adapt the model parameters to changes in the state of the environment, which is especially important when using such models in environmental monitoring systems. The fractal analysis method of time series is described, which allows finding the Hurst index for use in the developed forecasting models and determining the presence of long-term memory, cyclicity, etc., in the time series.

The complex forecasting model includes higher-order exponential smoothing, Holt, Winters, moving average, weighted moving average, and autoregressive models. All the parameters set in these models are related to the Hurst index, which is calculated based on the predictive fractal statistical analysis of the time series. The corresponding descriptions and justifications are given. Using such a model as part of an econometric system will help to predict and respond to possible changes in the values of pollution parameters more effectively. In particular, the persistence of the time series of pollution parameters may mean a stable upward or downward trend in pollution. Suppose the time series becomes close to random or ergodic. In that case, this may mean an emergency or that additional non-permanent emissions have appeared in the region that need to be monitored.

The third section describes a method for monitoring environmental pollution parameters based on a comprehensive model for predicting time series of pollution parameters with the use of statistical fractal analysis. The method considers the results of statistical fractal analysis to determine the direction of the time series trend, which may indicate whether the amount of pollution is increasing or decreasing in the short term. The method also determines the average cycle length based on the V statistic, which establishes the presence of long-term memory in the time series and determines the reliability of the trend forecast calculation.

In addition, the Hurst index determines whether emissions of harmful substances, particularly into the air, are stable. That is, it is shown that if the Hurst index of a time series indicates that the time series is close to random, the environmental situation in the area is unstable, and excessive emissions are possible. This means local governments and environmental services should respond to this situation to ensure environmental safety. The model for assessing the state of the environment in the monitoring system has been improved, which, unlike the known ones, takes into account the results of comprehensive forecasting of time series of pollution changes and can be a tool for ensuring environmental safety. The model establishes a comprehensive assessment of the state of the environment based on the method of monitoring environmental pollution parameters. The direction of developing an index of the state of the environment, based on the developed methods of monitoring and forecasting time series of pollution and characterized by the consideration of prospective pollution indicators, which can be used in urban environmental monitoring and conditions of environmental uncertainty, has been further developed.

The fourth section describes the information technology for monitoring environmental pollution parameters, which is distinguished by considering the results of analysis and forecasting changes in pollution parameters and offers an assessment of the state of the environment, which provides opportunities for quantitative assessment of the environmental situation in the region. Information technology includes methods for collecting information, a method for monitoring environmental pollution parameters, a model for assessing the state of the environment in the monitoring system, a method for calculating the environmental condition index, time series forecasting models, a method for statistical fractal analysis of time series, etc. All these components allow for a qualitative analysis of the region's environmental situation and predict its future change.

The information technology for monitoring pollution parameters based on a monitoring method that uses a comprehensive forecasting model, time series trend prediction, and statistical fractal analysis was verified. The verification was carried out on the example of a time series of environmental pollution parameters in different districts of Beijing, which were recorded from 2013 to 2017. The calculated errors in forecasting and assessing the state of the environment show the effectiveness of the development of such information technology and the relevance of this development for use by the city's environmental services and government agencies. Acts on implementing the results of work within the framework of research projects of Yancheng Polytechnic College (Appendix A).

The results obtained, both in theoretical and practical terms, serve as a basis for further scientific and applied research to improve and enhance various aspects of management and environmental monitoring. The author has published the main results in the following publications [1-11].

Personal contribution of the acquirer. The applicant personally received the main provisions and results of the dissertation work. Paper [1] describes the problem of environmental monitoring. Paper [2] formalizes the problem of assessing the state of environmental pollution. Paper [3] describes the hardware of the information system for environmental pollution monitoring. Paper [4] describes a method for monitoring environmental pollution parameters based on an integrated time series forecasting model. Paper [5] describes the requirements for the creation of information technologies for environmental monitoring. Other papers [6-11] describe some of the components of the dissertation research that were presented at international conferences. The work [6] was published in the edition indexed in the Scopus scientometric database.

Approval of the results of the dissertation. The main results of the work were reported, discussed, and received a positive evaluation at international conferences «Information technologies and interactions», Kyiv (2018, 2019), «Project Management in the Development of Society», Kyiv (2019), «Information Modeling Technologies, Systems and Complexes», Chernivtsi (2019), «Technology Development Management», Kyiv (2020), IEEE conference «Smart Information Systems and Technologies» (SIST-2021), Astana, Republic of Kazakhstan.

Publications. Based on the dissertation materials, 11 scientific works have been published, including: 4 scientific articles in specialized publications of Ukraine, 1 article in a publication that is not included in the list of the Ministry of Education and Culture, 6 materials of international conferences, one of them in a publication that is indexed by the Scopus database. The main results of the work were obtained by the author personally. Some of the scientific works published in co-authorship, the dissertation research describes those provisions resulting from the author's work.

Structure and scope of work. The dissertation consists of an introduction, four chapters, chapter conclusions, main conclusions, a list of references and appendices. The total volume of the dissertation is 141 pages, including 43 figures, 7 tables, a bibliography of 110 titles and 2 appendices.

CHAPTER 1. THEORETICAL FOUNDATIONS OF ENVIRONMENTAL POLLUTION MONITORING

1.1. The task of monitoring environmental pollution

Ensuring a balanced solution to the tasks of preserving a favorable environment, applying new approaches to environmental protection and observing the economic interests of both enterprises and the entire population requires a focused scientific approach. In recent years, there has been a close relationship between economic development and changes in the environment, and the mutual influence of the state of the environment on economic development and the results of economic activity on the state of the environment is growing.

In the face of a constantly deteriorating environmental situation, the scientific basis for managing anthropogenic impact, multifactorial analysis of pollution formation, combined with an operational forecast of pollution levels, is the only effective way to solve the problem.

Environmental pollution research includes the study of air pollution, groundwater and surface water pollution, soil pollution, and impact on the biosphere. Each type of pollution requires its models and research methods, as well as forecasting.

A meta-analysis of sources shows a significant increase in the international community's interest in studying environmental pollution. Most research publications on environmental pollution were made after 2012 [12, 13]. The primary purpose of these studies is to develop new methods for predicting the state of pollution, studying environmental monitoring systems and creating models of dependencies between pollution factors. At the same time, 60% of publications are devoted to forecasting, confirming this research area's prospects.

Fig. 1.1 shows the graph of changes in the number of scientific publications devoted to the study of environmental pollution found in the online version of the Science Citation Index (SCI-Expanded) from 1991 to 2017. The keywords used for the search were: ‘‘pollution’’, ‘‘pollutions’’, ‘‘polluted’’, ‘‘polluting’’, ‘‘pollutant’’, ‘‘pollutants’’, ‘‘pollute’’, ‘‘pollutes’’, ‘‘contamination’’, ‘‘contaminations’’, ‘‘contaminate’’, ‘‘contaminant’’, ‘‘contaminants’’, ‘‘contaminated’’, ‘‘contaminating’’, ‘‘estuary’’, ‘‘estuaries’’, ‘‘estuarius’’, ‘‘estuaria’’, ‘‘estuaries’’, ‘‘estuarial’’, ‘‘estuarian’’, and ‘‘estuarine’’.

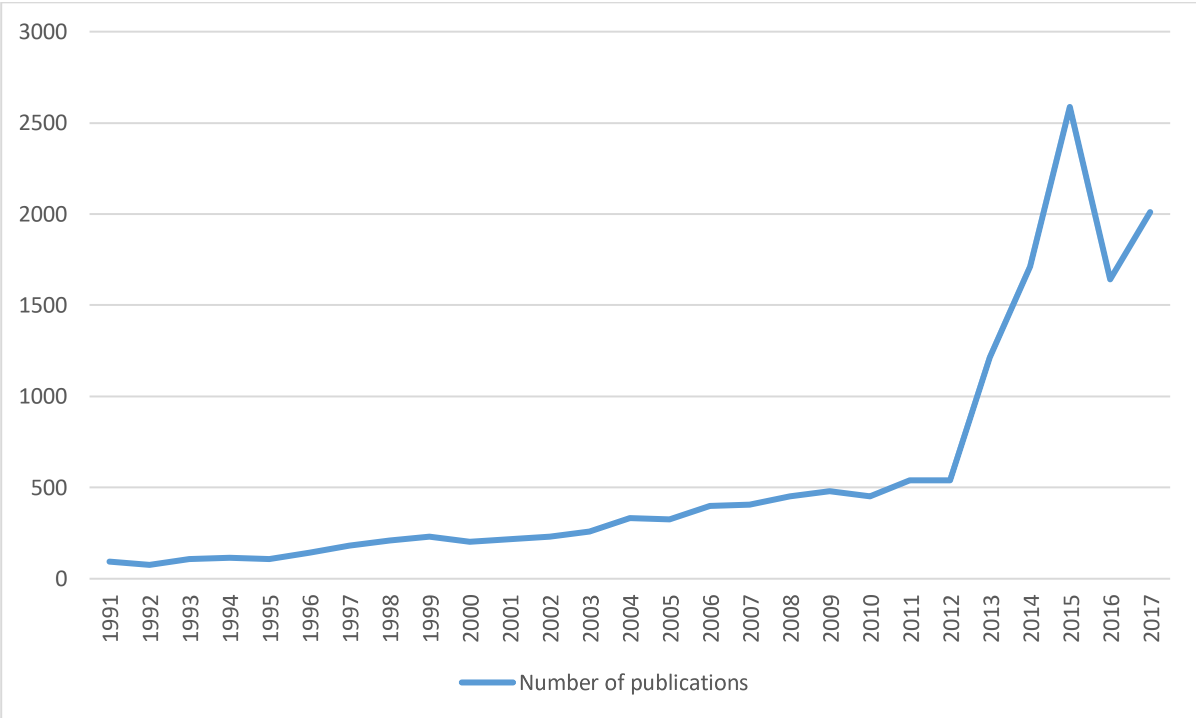


Figure 1.1. Graph of changes in the number of scientific publications devoted to the study of environmental pollution [13]

The importance of environmental protection research is also confirmed by the fact that governments of all leading countries spend an average of 0.8% of their budgets (more than $600 billion) on environmental protection measures [14]. Among these expenditures, R&D ranks third.

Environmental monitoring is systematically collecting, analyzing and evaluating data on pollution levels, air, water, soil quality, and other factors that may affect environmental sustainability and the health of people and ecosystems. Environmental monitoring consists of the following general stages:

1. Data collection. This may include the installation of sensors and instruments to measure various parameters, such as the level of dissolved oxygen in water, the concentration of heavy metals in soil, sound levels, and others.
2. Data analysis. Evaluation of the data obtained and determination of the state of the environment, identification of possible sources of pollution and their impact on the environment.
3. Reporting and informing. Preparation of reports on the results of monitoring and dissemination of information on the state of the environment to stakeholders, including government agencies, NGOs and citizens.
4. Action planning. Based on the monitoring results, develop strategies and measures to reduce pollution and maintain environmental sustainability.

Forecasting time series of pollution parameters is necessary for high-quality monitoring of the environment for the following reasons:

1. Early detection of trends. Predicting pollution dynamics allows to detect trends and identify possible changes in the state of the environment over time.
2. Planning of measures. Forecast data can be used to develop strategies and measures to improve the environment and reduce pollution.
3. Monitoring the effectiveness of measures. Comparison of predicted data with actual data allows to evaluate the effectiveness of the measures taken and adjust strategies as necessary.
4. Prevention of crises. Forecasting can help identify potential crises and take measures to prevent or minimize their consequences.

Thus, air quality monitoring methods and models are essential for various stakeholders interested in environmental protection, public health, and effective solutions to air pollution problems. Forecasting is a necessary element of the monitoring system, but it allows to identify undesirable trends in the environment in advance and correct them.

Environmental forecasting has three main classes: expert methods, modeling, and extrapolation methods [15]. In cases where the data cannot be formalized and structured, it is relevant to use expert forecasting methods. Expert forecasting methods for environmental pollution parameters involve qualified experts to assess and predict the pollution level. Experts can use their knowledge and experience to assess the impact of various factors on the environment and develop forecasts. The Delphi method can also be used in this case. This expert forecasting procedure involves an iterative process of interviewing a group of experts. Experts make their forecasts and then analyze and discuss the results to obtain agreed forecasts. The Mind Maps method is also used for this task. This graphical method allows experts to visualize and systematize information about various factors affecting environmental pollution and their possible consequences.

Using historical data or data from similar situations to predict future pollution levels is also a critical approach. In addition, the development of various scenarios is often used to predict possible levels of environmental pollution depending on various conditions and factors.

Extrapolation methods are most often used for short-term forecasts. These methods are based on the study of data, their quantitative and qualitative analysis for previous periods. In cases where the environmental situation is not subject to sharp changes, trends in the situation's dynamics for the next forecast period are determined. Recently, modeling methods using computer technology have become the most widely used.

There are three main approaches to forecasting the state of environmental pollution:

1. Works [16-18] use an approach based on pattern recognition using neural networks.
2. The possibility of using methods based on regression analysis is shown in [19-22].
3. The authors in [23] apply time series analysis methods, particularly trend forecasting methods.

The use of neural networks for environmental forecasting has a long history. In [16], five models of neural networks (NN), a linear statistical model, and a deterministic modeling system (DET) were compared to predict NO2 and PM10 concentrations in urban areas. The time series of NO2 and PM10 concentrations measured at two stations in the center of Helsinki from 1996 to 1999 on an hourly basis were considered. The data set required preliminary processing. Missing values were replaced to obtain a harmonized database. Comparisons were made using three criteria: the index of agreement (IA), the quadratic correlation coefficient (R2), and the fractional offset. The results obtained with different nonlinear NN models agree with the measured NO2 concentration data. In the case of NO2, the nonlinear NN models predict the crown concentration slightly better than DET. NN models perform better than the statistical linear model for predicting NO2 and PM10 concentrations. In the case of PM10, NN models were not as good as for NO2.

Paper [17] shows that modeling real-world processes, such as air quality, is a challenging task, both because of the chaotic and nonlinear nature of the phenomenon and because of the high dimensionality of the samples. Although neural networks have been successfully used in this area, the choice of network architecture still needs to be improved and more time-consuming when developing a model for a practical situation. The study proposes to use a parallel genetic algorithm (GA) for selecting input data and developing the architecture of a multi-layer perceptron model to predict nitrogen dioxide concentration at a high-traffic urban transport station in Helsinki. The results showed that the genetic algorithm is a suitable tool for solving practical problems of neural network design. However, it was noted that the evaluation of NN models is a computationally complex process, which sets limits for the application of this method. The authors also needed help tuning the GA parameters for the problem under consideration.

Paper [18] aims to compare two fundamentally different forecasting methods using a neural network. They are evaluated in terms of regression with periodic scalars. Self-organizing maps (SOM) are a form of competitive learning in which a neural network learns the data structure. It is shown that Multi-layer perceptrons (MLPs) are capable of learning complex relationships between input and output variables. In addition, the positive impact of removing periodic components on the quality of neural network training is shown. The methods were evaluated using a time series of NO2 concentrations. The estimated values for forecasting were calculated in three ways:

- using only periodic components;
- applying neural network methods to the residual values after removing periodic components;
- applying only the output data to the neural networks

The results showed that the best forecast predictions can be achieved by combining the periodic regression method and neural algorithms. However, the advantage of directly applying the MLP network to the raw data is not significant.

Another approach, which consists in applying Land use regression (LUR), is used by the authors in [19]. LUR is an interpolation technique that uses the interest of the polluter as a dependent variable using data on landscape, traffic, and physical environmental parameters as independent predictors. Two main limitations of this method are identified: the choice of independent variables in the process of model building and the fight against unbalanced repeated measurements. The authors propose circumventing these limitations by modeling a network that implements the machine deletion/substitution/addition (DSA) algorithm and using a generalized linear model to average unbalanced observations and measurements.

In [20], Support Vector Regression (SVR) is used to predict the Urban Air Quality Index (AQI) in China. This study aims to improve the forecasting results by minimizing the forecasting error of existing machine learning algorithms, considering multiple urban multivariate air quality data and weather conditions as input. The results show that in the case of multiple multivariate regression (MAPE), there is a decrease when there is a strong interaction and correlation of air quality characteristics with AQI. In addition, geographic location plays a significant role in predicting AQI.

A similar approach using Bayesian kernel machine regression (BKMR) to predict the impact of toxic mixtures is considered in [21]. The authors propose their own approach to selecting a hierarchical variable to identify essential components of the mixture and consider its correlated structure. Simulation modeling demonstrates the success of BKMR in identifying individual components of the mixture and predicting their interaction and distribution.

In [23], combined models of selective and hybrid types with time series indexing were developed to predict the level of air pollution in information and communication systems for environmental monitoring. Indexing in these models is based on the nearest neighbor method with selected metric distances. The described models allow achieving higher accuracy of short- and medium-term forecasting compared to the models included in the primary set of these combined models. The advantages of using these models in developing software and hardware systems are shown. When using specialized weather stations that can perform calculations, the IoT concept can significantly reduce the server load.

Study [24] examines urban and rural pollution in the Nansha River. This study is the first to consider pollution from point and non-point sources in the river watershed. A coupled model derived from the Environmental Fluid Dynamics Code and Water Quality Analysis Simulation Program was developed to simulate the hydrodynamics and water quality in the river. According to the characteristics of a typical urbanized river, three different PS and NPS management scenarios were developed and studied using simulation modeling. The authors faced the problem of the need to predict the water level in the river and the flow force, which introduced significant errors in predicting the ecological state of the river. Water pollution was also studied in [25, 26].

Paper [27] discusses the BFAST (Breaks For Additive Seasonal & Trend) method. This method combines methods for detecting changes in the behavior of time series with methods for decomposing series into components that determine trend changes, seasonal changes, and random components.

According to this method, the time series model looks like this:

$$Y_t = T_t + S_t + e_t, \tag{1.1}$$

where Y_t is the time series data recorded at time t;

T_t – trend component;

S_t is seasonal component;

e_t are residual, random components, $t = \overline{1, n}$, n is number of observations or number of elements in the image time series.

The residual components represent variations in the time series that characterize random deviations from the trend or seasonal components. In this model, the trend component is assumed to be piecewise linear, which means that it is specified in the form:

$$T_t = a_i + t \cdot b_I, \qquad (1.2)$$

where $r_{i-1} < t \le r_I$, $i = \overline{1, m}$ – control points of observation.

To determine the seasonal component, you can set a linear harmonic regression model:

$$S_t = \sum_{k=1}^{K} \left(\gamma_{jk} \sin\left(\frac{2\pi kt}{\lambda}\right) + \chi_{jk} \cos\left(\frac{2\pi kt}{\lambda}\right) \right), \qquad s(1.3)$$

where $\gamma_{jk} = \alpha_{jk} \cos \beta_{jk}$, $\chi_{jk} = \alpha_{jk} \sin \beta_{jk}$ are model coefficients.

The amplitude can be defined as

$$A_{jk} = \sqrt{\gamma_{jk}^2 + \chi_{jk}^2}, \qquad (1.4)$$

and the phase for the frequency $\frac{\lambda}{k}$ is defined as

$$\beta_{jk} = \frac{1}{tg\left(\frac{\chi_{jk}}{\gamma_{jk}}\right)}. \qquad (1.5)$$

The described model has the following advantages over the conventional seasonal model:

1. The model is less sensitive to short-term changes and noise.

2. A few observations are not required to calculate the parameters of the multiple regression model.

Applied models of geostatistical analysis were studied in [28]. The further development of these studies was the work [29], which investigated approaches to geostatistical modeling using variogram models. Studies on multivariate analysis, which allow for the selection of analysis options, are presented in [30]. Applied work on using geostatistical methods in the study of the environment and environmental problems is described in [31]. Most of the described methods are designed to work with continuous distributions of geostatistical indicators in the environment, so the mechanisms for processing discrete values need further improvement.

The analysis of publications shows that each proposed approach has advantages and disadvantages. In particular, methods using neural networks require significant computing power and time for training. However, this method provides the most accurate forecasts. Regression methods are computationally simple, but can only be used for short-term forecasts. It is also necessary to consider the explosive growth of available data in the XXI century and its insufficient quantity in previous periods. It should also be noted that forecasting pollution of various environmental components requires different approaches. Studies [24] have shown that the process of surface water pollution is stationary. The study also revealed a pronounced seasonal nature of fluctuations in all environmental indicators. The existence of a correlation between pollution indicators and meteorological indicators, in particular temperature and precipitation, is an undeniable fact. Studies also show a steady linear growth trend in Ukraine and China [24].

The peculiarity of air pollution is its ability to spread pollutants over vast distances and its significant dependence on weather conditions. Also, the atmosphere should be considered not only as a polluted environment but also as a mediator of anthropogenic pollution of other components of nature. The problem of anthropogenic and technogenic pollution is especially relevant in large cities with many industrial enterprises, vehicles and populations. Works [37, 18] analyzed the time series of 16 air pollutants and investigated their trend, seasonal, and random components (Table 1.1).

According to the identified patterns in the dynamic series, pollutants can be classified into three classes:

1. Substances with a pronounced seasonal component: benzopyrene, sulfur dioxide, carbon monoxide. This cycle is because in winter, the emissions of these pollutants from thermal power plants and motor vehicles increase significantly. Summer and winter periods affect the concentration of these pollutants in the air;

2. Substances with a pronounced trend: benzene, toluene, ethylbenzene, nitrogen oxide. In addition to the seasonal component, these pollutants have a pronounced upward trend in concentration.

3. Random values in which it is difficult to identify the seasonal component: trichloromethane, ammonia. Their level is influenced by random events (non-periodic processes, volley and accidental emissions, unfavorable meteorological conditions, etc.)

Table 1.1.

The time series of 16 air pollutants and investigated their trend, seasonal, and random components.

№	Pollutant	Contribution of the component		
		Trend	Seasonal	Random
1	Dust	0,0051	0,4891	0,5059
2	Sulfur dioxide	0,0435	0,4343	0,5222
3	Carbon monoxide	0,0378	0,4718	0,4903
4	Nitrogen dioxide	0,0193	0,4831	0,4976
5	Nitrogen oxide	0,0987	0,3987	0,5026
6	Hydrogen sulfide	0,0538	0,4481	0,4981
7	Phenol	0,0312	0,4589	0,5099
8	Hydrogen chloride	0,0430	0,4670	0,4900
9	Ammonia	0,0082	0,1828	0,8091
10	Formaldehyde	0,0796	0,4529	0,4675
11	Benzene	0,3368	0,3110	0,3523
12	Toluene	0,2585	0,3421	0,3995
13	Ethyl benzene	0,0907	0,3819	0,5274
14	Trichloromethane	0,0659	0,1296	0,8045
15	Benzopyrene	0,0237	0,4878	0,4886
16	Tetrachloromethane	0,0194	0,4352	0,5454

The use of trend models is possible only for forecasting the pollution level of substances of the first and second groups In addition, the study shows that the contribution of the random component to the structure of the time series of each group is large. This means that there are many hidden factors.

Given the above, we can assume that using neural network-based models in air pollution forecasting tasks is a good option. Neural networks can take into account hidden dependencies. Dynamic series form the basis for forming samples for training and testing neural networks.

Soil cover is a less dynamic and more buffering than atmospheric air or water bodies. One of the peculiarities of soil is that it accumulates information about the processes and changes that take place, and therefore not only indicates the state of the environment at a given time, but also reflects past processes. Soils play a protective role about natural waters, the atmosphere and vegetation. At the same time, while performing protective functions, soils can become the main source of many chemicals that pollute natural waters and are dangerous for plants. The redistribution of contaminants in the soil, and thus in adjacent environments (plants, water, and air), is caused by the movement of heavy metals through the soil profile. Unlike organic chemical pollutants that decompose over time, heavy metals can only redistribute between the components of the environment, and their decomposition periods can be many thousands of years [33].

The integrity of the soil-plant system points to the need to study plants as well in terms of the chemical impact of pollution on them. The protective capabilities of plants differ with respect to different pollutants: lead, for example, is retained on the roots, while cadmium easily penetrates into the ground organs. The nature of heavy metal uptake and accumulation by plants under pollution conditions is determined by the level of pollution, plant selectivity, and the impact of associated emissions that acidify or alkalize the soil solution. There is an undeniable connection between the chemical composition of plants and the elemental composition of the environment, but the direct dependence of heavy metal content in plants on the content in the soil is often broken due to the selective property of plants to accumulate elements.

Let's consider the possible impact of pollutants on human health, especially air pollution. Exposure to these air pollutants has both acute and chronic effects on human health, affecting a number of different systems and organs. These effects range from minor irritation of the upper respiratory tract to chronic respiratory and heart disease, lung cancer, acute respiratory infection, and asthma attacks [34, 35]. In addition, prolonged exposure to pollutants has also been linked to premature death and reduced life expectancy [36, 37]. To ensure air monitoring, air purifiers and monitoring systems are installed in cities [38-43]. Regarding the use of methods for estimating pollutant concentrations, most authors use a single method [44-50], while some studies combine several methods together to assess pollution at different scales [51, 52]. Some researchers not only estimate exposure to polluted air, but also examine the relationship with specific health outcomes [53, 54]. This thesis will focus on air monitoring.

1.2. Peculiarities of building systems for monitoring pollution of the scientific environment for environmental safety management

To obtain information on the dynamics of the content of harmful substances in the environment and to draw up maps of its pollution based on experimental data, it is necessary to measure the concentrations of pollutants in the air regularly. An automated information monitoring system (AIMS) is a system with a distributed organization of collection, processing, documentation and analysis of environmental parameters. In any environmental monitoring system, an AISM is an essential element and is designed to collect, process, and store information quickly and over the long term, forecast the state of the environment based on it, and provide information to local information centers, the management of enterprises and their environmental protection departments, and other information users. AISM provides the following functions:

- automatic measurement of monitored parameters;

- collection of information and its primary processing;

- control of deviations of current values of these parameters from their reference levels;

- display of information and formation of the operational situation;

- documentation of information;

- forecasting changes in the environment;

- transfer of information to interested parties and adjacent systems.

An automated control system (ACS) called Ecoinspector has been introduced in Ukraine [55]. This ACS is a comprehensive solution that includes hardware and software that can be divided into three parts:

- software for mobile devices and sensors for monitoring the parameters of the built environment, which performs the functions of registering information and taking samples and measurements performed directly at the monitoring site

- server software that performs data storage and processing functions;

- software for a regular personal computer for other operations.

The system is based on a set of subsystems for processing data from one analytical department of the regional and national environmental inspectorate. The national-level software additionally has a set of subsystems for importing data from all analytical departments into a single database, as well as for processing them and generating various reports.

The complex of subsystems for data processing of the environmental inspection analytical department consists of four subsystems:

- The Emissions subsystem is designed to accumulate, process and analyze data on emissions from stationary sources of air pollution;

- Soils and Waste subsystem, designed to accumulate, process and analyze data on waste from pollution sources and the state of soil pollution;

- Water and Discharges subsystem, designed to accumulate, process and analyze data on wastewater discharges and the state of natural waters, mainly surface waters;

- a subsystem for registering information on sampling and measurements performed directly at the monitoring site.

The results of the system can be seen in real-time using an interactive map of environmental monitoring [56], which is available on the website of the Ministry of Ecology and Natural Resources of Ukraine (Fig. 1.3).

Similar environmental monitoring systems operate around the world, including the air pollution monitoring system in China (Fig. 1.4), which became the basis for the international project The World Air Quality Index [57].

Figure. 1.2. An interactive map of environmental monitoring on the example of the Inspector Meteo system

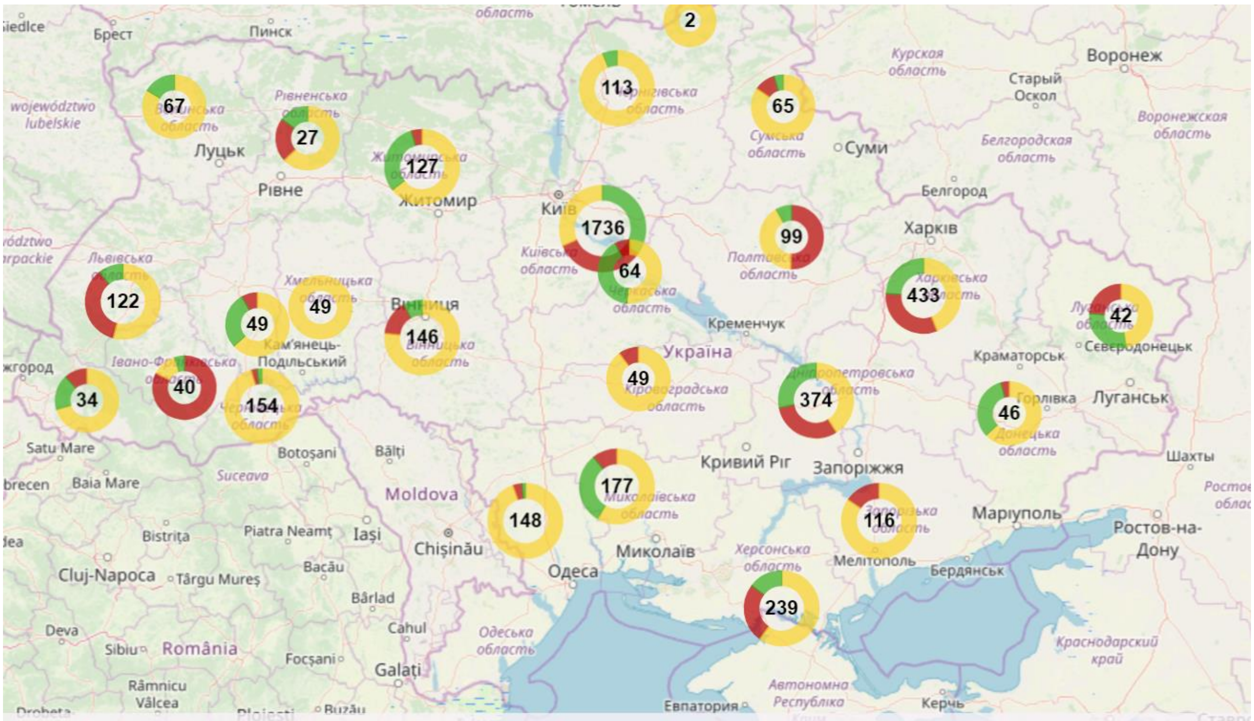


Figure. 1.3. Interactive map of monitoring environment of the environment

The traditional approach to environmental monitoring involves observation points and centralized data processing. This approach is only sometimes economically feasible. Distributed networks are a concept in which individuals, groups, and communities are actively involved in collecting data to build a knowledge base. This is mainly done in two ways: using an extensive sensor network and using available devices (e.g., mobile phones) to create ad hoc networks. Positive experience with this approach is known in India and Pakistan:

1. Using the mobile phone based application user is able to report any nearby incident of environment pollution or hazard by taking a photo or video of the problem and submitting it to the server. Each report is tagged using some meta information and location using positioning system provided by GPS of the mobile phone.

2. In the medium tier, the server collects the information, categorize and analyze the information posted by end-users automatically using intelligent algorithms. The end-users are able to watch and support the reports submitted by other users.

3. The application in the third tier help the municipality governing authority to monitor and detect potential threats (short term and long-term) by visualizing them based on meta-information and community trust and the application will help them to take decisions based on an expert decision system.

The use of new approaches such as participatory sensing will reduce the financial costs and involve existing technical means for monitoring and forecasting the state of the environment.

An important issue is the technical component of obtaining data on the state of the environment. In [58], the work classified the known monitoring networks into three classes based on the characteristics of the sensors: Static Sensor Network (SSN), Community Sensor Network (CSN), and Vehicle Sensor Network (VSN). Comprehensive reviews and comparisons of these three types of sensor networks have also been conducted, revealing their significant limitations. A real-time system with high spatio-temporal resolution can solve the problems of limited data availability and poor scalability of conventional pollution monitoring systems. The authors propose the concept of The Next Generation Air Pollution Monitoring System (TNGAPMS) based on the use of deep perception, MicroElectroMechanical Systems (MEMS) and Wireless Sensor Network (WSN) technologies. However, it also has limitations in terms of the need for 3D data collection capabilities and the flexibility of the sensor network.

Low-cost sensor technologies have the potential to revolutionize the field of air pollution monitoring by providing high-density air pollution data. Such data can complement traditional pollution monitoring, improve impact assessments, and raise community awareness of air pollution. However, data quality remains a significant challenge that hinders the widespread adoption of low-cost sensor technologies. Unreliable data can mislead users and potentially lead to alarming consequences, such as reporting acceptable levels of air pollutants when they exceed limits recognized as safe for human health [59, 60]. Paper [61] addresses the efficient deployment of low-cost sensors while ensuring sufficient data quality. For large sensor networks, where conventional calibration checks are impractical, statistical methods of data quality assurance should be used. There is a need to develop mathematical and statistical methods for sensor calibration, fault detection, and data quality assurance.

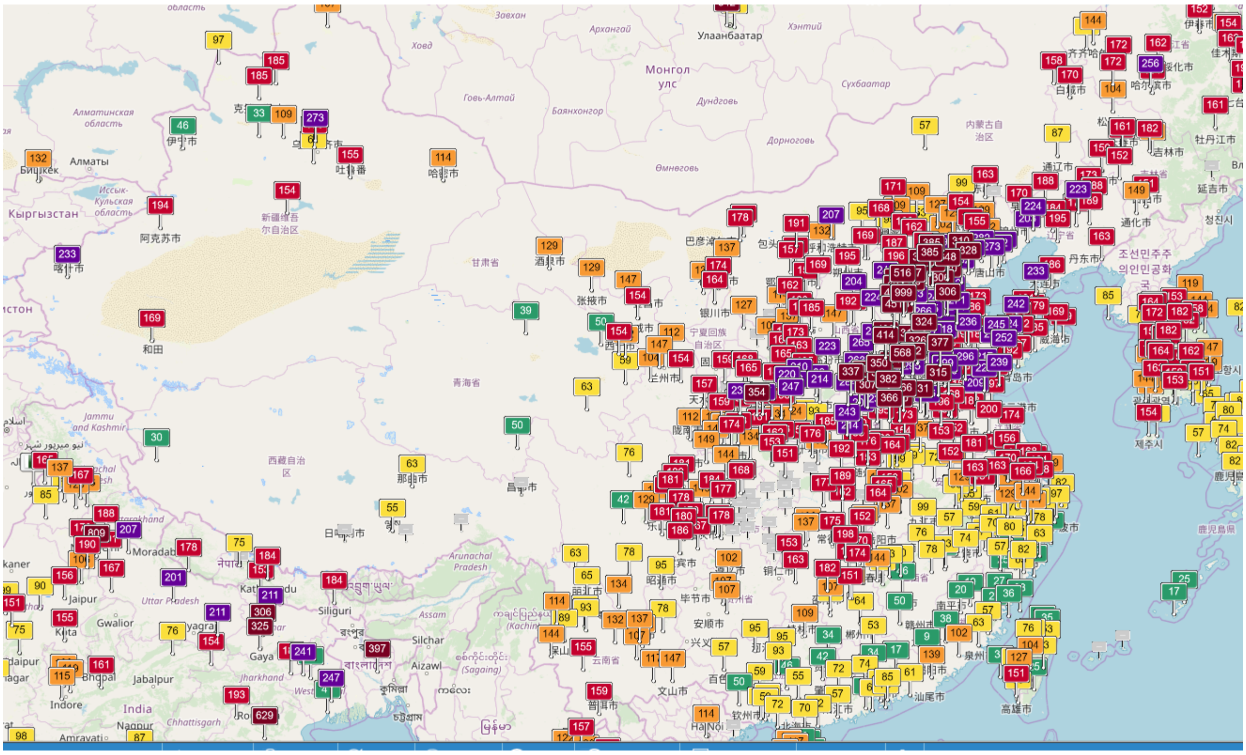


Figure. 1.4. Air Pollution in China: Real-time Air Quality Index Visual Map

Water monitoring is a much more expensive and technologically complex process. Thus, a bioelectronic nose was described for real-time water quality assessment [62]. The nose is built on the principle of a human olfactory receptor based on a single-walled carbon nanotube field-effect transistor (swCNT-FET). The bioelectronic nose can selectively detect Geosmin (GSM) and 2-methylisoborneol (MIB) in low concentrations. The main problem of this sensor is the need to use a carbon nanotube field-effect transistor.

Paper [63] discusses nanomaterials used for water quality monitoring, particularly nanomaterials used to detect traces of pollutants and pathogens. These nanomaterials include carbon nanotubes, magnetic nanoparticles, noble metal nanomaterials, and quantum dots.

The authors of [64] note that accurately recognizing the sources and pathways of transport of various substances in the catchment area is significant for any management activity. This task can be solved on small and medium scales by using online measurements with high temporal resolution. This paper proposes an approach that uses mobile measurement stations to provide real-time monitoring of various parameters. The problem arises of combining commercially available sensors and wet chemical analyzers into a new set.

A technical report on water monitoring tools was developed as part of the Water Framework Directive (WFD), 2000/60/EC study [65]. It identifies potential exposure-based tools (e.g., biomarkers and bioassays) that can be used in different monitoring programs (surveillance, operational and investigative) that link chemical and ecological status assessment.

Levels of trace element contamination in surface soils can be assessed using soil analysis and leaching tests. However, a significant problem is the collection of soil samples and their transportation to the laboratory. in China, there are three national monitoring programs: MEP, MLR, and the Ministry of Agriculture [66].

Study [67] proposes an alternative method for using lichens to monitor and assess trace element contamination in surface soils. Lichens growing in abandoned mine sites and uncontaminated areas of southwestern Japan and their substrates were analyzed using inductively coupled plasma-mass spectrometry and X-ray fluorescence spectrometry to determine the relationships between the concentrations of Cu, Zn, As, and Pb in lichens and soils, including their absorption properties. The concentrations of these elements in lichens were positively correlated with those in soils, regardless of lichen species, location, habitat, or soil conditions. The analyzed lichens had neither competitive nor antagonistic properties in elemental uptake, which made them good biomonitors of trace element pollution in surface soil. The distribution maps of the average concentrations of Cu, Zn, As and Pb in each sampling area revealed almost all soil contamination with Cu, Zn and As. Therefore, lichens can be used in practical applications to monitor Cu, Zn, and As contamination in surface soils.

Let's consider the problem of estimating environmental pollution in two formulations: point and plane. Let's assume it is necessary to estimate environmental pollution at a certain point. A set of indicators can estimate environmental pollution. Let

$$R = (r_1, r_2, \dots, r_n), \tag{1.6}$$

is a vector of real numbers describing the state of the environment, where n is the number of indicators. Each vector coordinate is a specific indicator, for example, the concentration of sulfur dioxide or carbon monoxide in the air, the concentration of nitrates in water, etc. The relevant indicators can be obtained both with the help of appropriate technical means (weather stations, mobile and stationary sensors, etc.) and with the help of services.

The state of the environment is not a stationary value and changes over time. Therefore, environmental indicators should be considered as time-dependent functions. That is.

$$R(t) = (r_1(t), r_2(t), \dots, r_n(t)), \tag{1.7}$$

where t is a certain time. For the sake of simplicity, we will assume that the indicators are updated with a certain period of time (hourly, daily, monthly). Then, without limiting the generality, we will consider time as a discrete value. That is

$$t_i = t_0 + \Delta t^\circ i, \tag{1.8}$$

where t_0 is the initial moment of time from which the environmental state is observed, Δt is the frequency of observation, and a $i = \overline{1, m}$, where m is the number of observations.

Let's define $r_j(t_i)$ as r_j^i. Then

$$R(t_i) = (r_1(t_i), r_2(t_i), \dots, r_n(t_i)) = \left(r_1^i, r_2^i, \dots, r_n^i\right). \tag{1.9}$$

Then the task of assessing environmental pollution can be divided into the following stages:

1. Collecting data on the history of environmental pollution.
2. Observation of the current state of the environment.
3. Forecasting the state of environmental pollution in the future.

To solve the first task, building a database that stores the history of environmental pollution is necessary. There are two possible ways of storing it. The first way is to store the history of the state of the environment as a set of dynamic series, each of which reflects the change in one indicator. The second way is to save a sequence of vectors, each of which reflects the state of the environment at a certain point in time.

The second task requires a data source, a data transmission channel, and methods for converting information. The source of environmental data can be either hardware or other environmental monitoring services. The data transmission channel depends on the data source. Most often, the transmission channel is the Internet, but sometimes, it is necessary to transmit data through service protocols, such as Zigbee [59, 60], to a form in which it can be stored in the system described in the first task.

Consider the third problem for the case when only one indicator needs to be forecasted. Then the forecasting task is to calculate the values of the pollutant indicator with a horizon $\theta>1$, i.e. for each time point m+1, m+2, ... m+ θ. In other words, it is necessary to continue the dynamic series of pollution indicators:

$$R^* = (\overline{r}_{n+1}, \overline{r}_{n+2}, \dots, \overline{r}_{n+\theta}), \tag{1.10}$$

where the horizon θ is fixed before the forecast is calculated.

Let p be the size of the retrospective sample, i.e., the size of the area of the time series immediately following the point at which the forecast is calculated (point t_m), and which is involved in calculating the forecast values for p<m. The functional relationship on the basis of which the values are predicted is called a forecasting model. Moreover, $\overline{r}_{n+\tau}$ is the predicted estimate calculated at point r_n for τ points ahead with period $\tau = \overline{1, \theta}$. If we formally denote such a model as f, then the forecast calculated at point r_n for one point ahead or with a period of 1 can be defined as follows: $\overline{r}_{n+1} = f(r_{n-m+1}, r_{n-m}, \dots, r_n)$.

As shown earlier, various forecasting models can be used for forecasting: regression, trend, neural network, etc. It was also shown that different models should be used for different environments of environmental indicators. Therefore, an important task is to build a method that takes into account a priori and a posteriori information and allows to improve the quality of the forecast by choosing a forecasting model that is better suited to a particular case.

The problem of assessing environmental pollution in a plane setting has much in common with a point setting. Similarly, the task consists of three stages: collection, observation, and forecasting.

The key difference in this setting is the presence of a whole observation network. Then the information about the state of the environment can be described as a set of tuples $\langle R_i, C_l \rangle$, where R_i is a vector reflecting the state of environmental pollution indicators at time t_i, and C_l is information about the location where the relevant data were obtained. They are set in a specific coordinate system. It should also be noted that a significant part of the methods of forecasting and searching for the existence of a relationship between the greatnesses on the plane are based on the assumption that the coordinates are set in the Cartesian system. Observations of the state of the environment are linked to geographic coordinates.

The geographic coordinate system is used to determine the position of points on the earth's surface relative to the equator and the initial (zero) meridian. The coordinates are angular quantities: geographic latitude B and geographic longitude L. Longitude (the angle between the meridian plane at the point of observation and the zero (Greenwich) meridian), latitude (the angle between the straight line and the equator plane) determine the position of the point on the Earth's surface. Measured in degrees (°), longitude is from 0° to 180° west and east of Greenwich, latitude is from 0° to 90° north, from 0° to -90° south of the equator.

The geographic coordinate system is spherical. Therefore, a conversion formula should be used to convert to the Cartesian system. Considering all the above, the information system should include the following subsystems:

1. Subsystems for collecting information about the state of the environment. This subsystem includes hardware for measuring environmental indicators, APIs for importing from other environmental monitoring systems, and methods for converting data to a single format used in the data storage subsystem.

2. Data storage and accumulation should be optimized considering the specifics of the data to be stored.

3. The environmental forecasting subsystem includes forecasting models and methods for selecting which model should be used in a particular case to achieve greater forecasting accuracy.

4. The user interaction subsystem is one of the most essential parts of the information system. It should present information in a convenient form. In particular, the presentation of reports, interactive maps of the state of the environment, and recommendations on dangerous changes in environmental factors, such as exceeding the maximum permissible concentrations of certain pollutants.

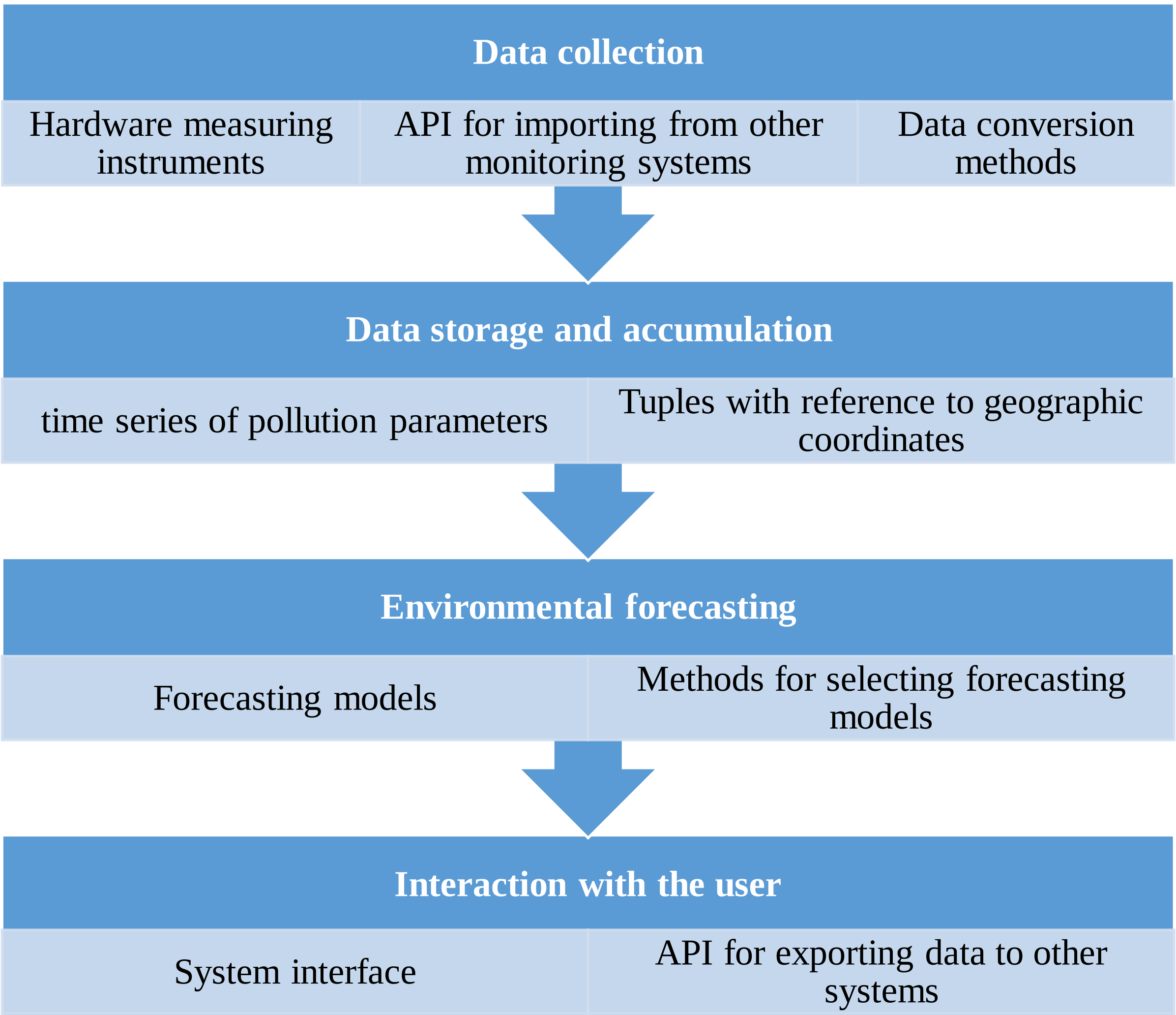


Figure 1.5. Conceptual diagram of the environmental monitoring system.

Each subsystem can be considered as a separate module. The system's modular structure will allow you to expand and modify the capabilities of each module independently of the others. The modular structure also increases the stability and flexibility of the system. Given the modern approach to software development, the modular approach allows you to implement a microservice approach when the system consists of a set of independent microservices.

Another modern approach to creating air monitoring systems is wireless sensor networks. Papers [68-82] consider the features of creating and using such networks for environmental monitoring.

It is indicated that constructing an air pollution monitoring system is also essential for the whole and safe operation of some critical infrastructure facilities, including power plants, processing and chemical plants, airports, tunnels and subways, etc. In case of poor environmental measurement near or inside these facilities, irreparable consequences for many people's environment, health and lives can occur. Since these facilities are critical infrastructure, they must operate around the clock. In addition, the air, soil, water, etc., near these facilities should be monitored around the clock. Thus, another critical confirmation of the relevance of this work is the application of its results in critical areas of state activity, such as the safe operation of critical infrastructure facilities.

Pollution caused by chemical plants and processing facilities is a severe problem in China. These industrial sectors often release harmful substances into the atmosphere, water sources, and soil, negatively impacting the environment and human health. For example, hazardous emissions may contain toxic chemicals such as mercury, chlorine, sulfur dioxide, etc. These substances can lead to air, water, and soil pollution, causing serious problems for human, animal, and ecosystem health.

The Chinese government has taken various measures to control and reduce pollution from chemical plants and processing facilities. These measures include imposing strict emission standards, promoting wastewater and emission treatment technologies, and conducting inspections and training for employees on environmental standards.

Many of China experience chronic air pollution with high concentrations of delicate particulate matter (PM), particularly PM2.5 [83,84]. PM2.5 refers to fine PM with an aerodynamic diameter of less than 2.5 microns. The North China Plain (NCP), which surrounds Beijing, experiences the worst air pollution, with excessive concentrations of PM2.5. To address the smog, China's State Council has set a target of a 25% reduction in PM2.5 emissions for the NCP by 2017 compared to 2012 levels, as well as a specific target of no more than 60 μg m-3 for the average annual Beijing.

Studies [85-89] show that observed air pollution data are mixed with meteorological fluctuations. Considering this information allows us to get a more complete picture of Beijing's PM2.5 pollution. According to official air quality statistics, in 2016, the annual concentration of PM2.5 in Beijing decreased by 9.9%. The paper [89] analyzes PM2.5 pollution over the past four years at 36 monitoring sites and meteorological data for the past seven years.

Despite these measures, the problem of industrial enterprises' pollution remains a pressing issue in China, and continued efforts to address it are an essential aspect of the country's sustainable development.

Conclusions to chapter 1

1. The basic concepts and features of environmental monitoring are considered. The necessity of increasing monitoring efficiency and the main approaches to their solution by improving methods and technologies are substantiated. The analysis of the properties of time series of pollutants shows that they can be classified into three classes: substances with a pronounced seasonal component, substances with a pronounced trend, and random variables. This classification allows for better selection of forecasting and data transformation methods that can be more effectively applied to each class of substances.

2. The problem of environmental monitoring is formalized in two formulations: point and plane. The main stages of environmental monitoring are highlighted. These are collecting data on the state's history, monitoring the current state and predicting the state of environmental pollution in the future. Approaches and requirements for technical means at each stage are proposed. A review of known systems for monitoring air, water and soil pollution. The importance of the technical component is shown. Fundamental differences and new trends in using innovative technologies for monitoring environmental pollution parameters are identified.
3. A scientific hypothesis has been formulated that defines the author's vision of environmental monitoring organization in terms of combining software and hardware systems and using trend models to predict environmental pollution parameters. By formalizing the problem of environmental monitoring, the structure of the information system for environmental monitoring is proposed. The information system should include the following subsystems: a subsystem for collecting information about the state of the environment, a subsystem for storing and accumulating data, predicting the state of the environment, and a subsystem for user interaction.
4. It is indicated that constructing an air pollution monitoring system is also essential for the whole and safe operation of some critical infrastructure facilities, including power plants, processing and chemical plants, airports, tunnels and subways, etc. In case of poor environmental measurement near or inside these facilities, irreparable consequences for many people's environment, health and lives can occur.

CHAPTER 2. BUILDING A MODEL FOR FORECASTING TIME SERIES OF ENVIRONMENTAL POLLUTION PARAMETERS

2.1. Construction and features of time series of environmental pollution parameters

Let's consider the peculiarities of constructing and characterizing time series of environmental pollution parameters. In general, time series of environmental pollution parameters have some peculiarities due to their specific nature and time dependence. This should be considered when planning and designing a forecasting model and a monitoring system for pollution parameters. The main features to pay attention to are:

1. Seasonality. Pollution parameters, such as air or water pollution levels, can vary depending on the time of year. For example, the level of air pollution may be higher in winter due to the heating season or in summer due to the use of cars. This is important to consider when analyzing time series.

2. The presence of a trend. Time series of pollution can reflect general trends in pollution levels over time. For example, pollution may increase or decrease over time due to industrialization, environmental measures, etc.

3. The presence of cyclicality. In addition to seasonality, there may be longer-term cycles in pollution associated with economic or technological cycles, policy changes, or other factors.

4. The presence of random fluctuations. The environment is subject to various random factors, such as natural disasters, accidents, response to environmental protection measures, etc. These fluctuations can cause significant deviations from typical trends or seasonality.

When conducting a pre-prognostic analysis of the time series of environmental pollution parameters, it is necessary to check these features. Let us consider in more detail why these characteristics appear and formalize the time series of environmental pollution parameters.

Seasonality in the time series of environmental pollution parameters is manifested in systematic fluctuations in the pollution level due to changes in weather conditions, climatic factors, social factors, and other seasonal changes. Seasonality is particularly evident in winter air pollution. During the colder months, air pollution, especially heating-related pollution such as emissions from boilers and furnaces, can increase significantly. For example, large cities may experience an increase in air pollution in winter due to the use of heating systems. Seasonality can also be manifested in emissions from motor vehicles. In the summer, vehicle emissions may increase due to more vehicles on the road during vacations and holidays. For example, tourist areas may see an increase in air pollution during the summer months. Seasonality is evident in water pollution, for example, during spring or summer storms. Heavy rains can cause pollution of water bodies with runoff from urban areas containing pesticides, oil products, and other pollutants.

Regarding cyclicality, the time series of environmental pollution parameters may show longer and less regular changes than seasonal factors. These cycles can be related to various economic, social, or technical factors that affect environmental pollution. Standard cycles that affect the process of generating this time series include economic, technological, political, and social cycles.

Economic fluctuations can affect pollution levels by changing industrial activity and consumer behavior. For example, during periods of economic downturn, pollution levels may decrease as businesses reduce their output and emissions. Technology cycles are related to changes in technology and industrial processes that can lead to cyclical changes in emissions and other pollution parameters. For example, introducing new emission reduction technologies can cause cyclical pollution-level changes over time. Less intense but still influential changes in the legal environment and environmental policy can also lead to cyclical changes in pollution levels. For example, a change in government or policy may change the level of regulation of industrial emissions or air and water quality standards. Changes in consumer attitudes and habits can also impact pollution levels. For example, increased awareness of environmental issues may reduce the use of harmful materials or transportation.

Trends in the time series of environmental pollution parameters are manifested through the general long-term direction of changes in pollution levels. This trend can be relatively stable, increasing or decreasing over a certain period. In this case, a gradual increase may be observed. For example, an increase in the concentration of carbon dioxide in the atmosphere due to emissions from industry and transportation. The trend may also gradually decrease. For example, measures to regulate exhaust gas emissions from factories can decrease air pollution. In some cases, there may be a trend of stability, where the pollution level remains almost unchanged over time. For example, if emissions from cars have remained constant for several years.

Random fluctuations in the time series of environmental pollution parameters are manifested as unpredictable, random fluctuations in pollution levels that do not have a clear systematic or regular pattern. Various factors and events, such as natural disasters, unexpected technical problems, accidents, or other random events, can cause these fluctuations. Although a component of random fluctuations is present in any pollution time series, the transformation of such a time series into a random series may indicate the occurrence of an extreme event for example, large forest fires may lead to a sudden increase in air pollution levels of harmful substances such as smoke and ash particles. Also, such series are formed due to accidents at industrial facilities that lead to emissions of harmful substances, such as a chemical spill from a plant or an oil leak from an oil pipeline, etc. Identifying the moment when the random component in the structure of the time series of environmental pollution parameters increases can help implement a pollution monitoring system.

Let's carry out a mathematical formalization of the problem considered in this thesis. Let the discrete set

$$T = \{t_1, t_2, \ldots, t_n\}, \tag{2.1}$$

then

$$Q=\left(q\left(t_1\right),q\left(t_2\right),\ldots,q\left(t_n\right)\right), \qquad (2.2)$$

where Q is time series of the level of environmental pollution, which reflects the quantitative indicators of pollution parameters that are recorded at the moment of time $t_1,t_2,\ldots,t_n$ as a finite sequence of measurements, the initial time is denoted by t_1, the current moment of time is denoted by t_n, $t_1,t_n \in T$, $n \in \mathbb{N}$. Let's assume that the level of environmental pollution is determined at fixed points in time, i.e., day, week, month, year, etc. For this purpose, you can use appropriate sensors. The measurement results are real numbers $q\left(t_r\right) \in \mathbb{R}$, $r=\overline{1,n}$.

A forecasting method is a sequence of prognostic operations and actions that ensure the construction of a forecasting model based on the estimates of the accuracy of forecast values. The most common forecasting methods include extrapolation, interpolation, expert opinion, mathematical modeling, etc. The task of a forecaster is to choose a method that would fully meet the forecasting goal and provide the required accuracy.

A forecasting system is a system of methods that function by the principles of forecasting, i.e., meet the following requirements: systematic and interconnectedness of forecasts, continuity, adequacy of forecasts to the object of study, efficiency, variability, etc.

Time series analysis involves the implementation of two main stages, which determine the purpose of the analysis:

1. Study of the time series structure or pre-prognostic analysis. This stage involves preliminary data processing and identification of special characteristics that are directly used to build an adequate forecasting model.
2. Building and evaluating a time series forecasting model.

The basic concepts of the theory of time series forecasting are defined in [90 - 98].

A time series can be represented as a function with three components: trend, seasonality, and randomness:

$$q\left(t_r\right)=f\left(A_r,S_r,V_r\right), \qquad (2.3)$$

where A_r - trend component of the time series, S_r - seasonal component of the time series, V_r - random component.

We can specify two models for a time series that combines these components: multiplicative and additive:

$$q(t_r) = A_r \cdot S_r \cdot V_r,\ r = \overline{1,n} \tag{2.4}$$

$$q(t_r) = A_r + S_r + V_r. \tag{2.5}$$

In the case of a multiplicative model, you can switch to an additive model by logarithmic transformation:

$$\log(q(t_r)) = \log(A_r) + \log(S_r) + \log(V_r),\ r = \overline{1,n}. \tag{2.6}$$

The traditional representation of a time series is an autoregressive model in which the values of $q(t_r)$ is determined on the basis of the previous value of the series, taking into account the influence of random factors AR (2.7):

$$q(t_r) = \lambda_1 q(t_{r-1}) + \lambda_0 + V_r,\ r = \overline{2,n} \tag{2.7}$$

Another model that takes into account the two previous values is called the AR (2.8):

$$q(t_r) = \lambda_1 q(t_{r-1}) + \lambda_2 q(t_{r-2}) + \lambda_0 + V_r,\ r = \overline{3,n}. \tag{2.8}$$

An important characteristic for generalizing a time series of environmental pollution parameters is the autocorrelation function. The autocorrelation function (ACF) of a time series shows the relationship between the values of the series and its lags (delays) at different time intervals. In other words, the ACF measures the degree of correlation between the values of a series at certain time points and their lags by a certain number of time units:

$$\mathrm{ACF(Q)} = \mathrm{Corr}(q(t_r), q(t_{r-k})),\ k = 1, 2, \ldots \tag{2.9}$$

ACF is used to determine whether there is autocorrelation in a time series, i.e. whether there is a relationship between the values of the series at different time points. Autocorrelation can be positive (if the values increase together) or negative (if the values decrease together). The closer the value of the autocorrelation function is to 1 or -1, the stronger the autocorrelation. For example, suppose we have a daily time series of temperatures. In that case, we can use the autocorrelation function to check if there is a correlation between the temperatures today and those of previous days. If the autocorrelation value is close to 1 for 1-day trackings, this may indicate the presence of autocorrelation, meaning that temperatures tend to vary over several days. In general, the ACF provides information about the type and structure of correlation in a time series and can be used to model and forecast that series.

ACF helps to identify the presence of seasonal dependence in environmental pollution. This can help identify different seasonal patterns in pollution, such as increased pollution in winter due to the heating season or during the summer season due to increased tourist activity.

The autocorrelation function can indicate the presence of trends in pollution, such as a gradual increase or decrease in pollution levels over time. This helps determine long-term trends in pollution.

ACF can also identify correlations between pollution values at different time intervals. This allows you to find out whether there are local patterns in pollution, such as the relationship between emissions from certain sources and their impact on environmental quality in certain periods. Based on the autocorrelation function, models can be built to predict future pollution values and identify effective pollution reduction strategies. Thus, the autocorrelation function can provide important information about environmental pollution parameters' characteristics and time series dependencies.

To understand the structure and features of the time series of pollution indicators, in addition to the autocorrelation function, it is necessary to conduct a comprehensive analysis of the time series structure, understand the presence of trend and random components and their strength, and determine the presence of memory in the time series. The presence of memory will define the time series as one that retains information about the initial conditions and the trend that is recorded in it will be preserved. If the random component increases, we can say that there are changes in the level of environmental pollution, and new pollutants or pollutants may appear. This is essential information for building a system for monitoring and forecasting the state of the environment.

2.2. The method of predictive statistical analysis of time series

In this paragraph, we will discuss the method of predictive statistical analysis of time series of environmental pollution parameters. A universal tool that can be used for predictive analysis and integrated into an environmental monitoring system is fractal time series analysis [99-106].

In this case, the time series of environmental pollution parameters

$$Q=\left(q\left(t_1\right),q\left(t_2\right),\ldots,q\left(t_n\right)\right) \tag{2.10}$$

is divided into accumulative rows of views:

$$Q^h=\left(q\left(t_1\right),q\left(t_2\right),\ldots,q\left(t_h\right)\right),\ h=\overline{3,n}, \tag{2.11}$$

then

$$Q^3=\left(q\left(t_1\right),q\left(t_2\right),q\left(t_3\right)\right), \tag{2.12}$$

$$Q^4=\left(q\left(t_1\right),q\left(t_2\right),\ldots,q\left(t_4\right)\right), \tag{2.13}$$

$$\ldots$$

$$Q^n=\left(q\left(t_1\right),q\left(t_2\right),\ldots,q\left(t_n\right)\right). \tag{2.14}$$

For each time series $Q^3,Q^4,\ldots,Q^n$ calculate the arithmetic mean using the formula:

$$\overline{Q}^h=\frac{\sum_{j=1}^{h}q\left(t_j\right)}{h}, \tag{2.15}$$

or

$$\overline{Q}^3=\frac{q\left(t_1\right)+q\left(t_2\right)+q\left(t_3\right)}{3}, \tag{2.16}$$

$$\overline{Q}^4=\frac{\sum_{j=1}^{4}q\left(t_j\right)}{4},\ \ldots,\ \overline{Q}^n=\frac{\sum_{j=1}^{n}q\left(t_j\right)}{n}. \tag{2.17}$$

Then let's calculate the deviation using the formula:

$$\rho(h,s)=\sum_{j=1}^{s}\left(q(t_j)-\overline{Q}^h\right),\ h=\overline{3,n},\ s=\overline{3,n}, \qquad (2.18)$$

from here we find the range:

$$F_h=\max_{s=\overline{1,h}}\rho(h,s)-\min_{s=\overline{1,h}}\rho(h,s), \qquad (2.19)$$

then the standard deviation is determined by the formula:

$$\sigma_h=\sqrt{\frac{1}{h}\sum_{j=1}^{s}\left(q(t_j)-\overline{Q}^h\right)^2}\ ,\ h=\overline{3,n}, \qquad (2.20)$$

if

$$\Delta_h=\frac{F_h}{\sigma_h},\ h=\overline{3,n}, \qquad (2.21)$$

then consider the equation:

$$\lg(\Delta_h)=H\lg(h)+\lg(\delta), \qquad (2.22)$$

where H is Hurst's index, as a coefficient on the independent variable, which is determined by the least squares method, $\delta=\text{const}$.

By calculating the Hurst exponent of the time series of environmental pollution parameters, it is possible to determine the presence of memory in the time series, i.e. the presence of long-term dependence and the presence of cyclic components. The latter can be identified by analyzing the V statistic. The growth of this statistic with an increase in the number of observations indicates the trend stability of the time series or persistence, and stabilization or decrease indicates an increase in the influence of random factors. A sharp change in the trend from increasing to decreasing may indicate the transformation of the series into white noise, which may be characteristic of an emergency in the change in the level of environmental pollution:

$$V_h=\frac{\Delta_h}{\sqrt{h}},\ h=\overline{3,n}, \qquad (2.23)$$

where V_h - value V of the statistics recorded for the time series Q^h.

Let's consider possible options for interpreting the results of a predictive statistical analysis of a time series of environmental pollution parameters based on fractal analysis. The scheme of interpretation of the results can be as follows:

1. If the Hurst's index of the time series $H\left(Q^h\right) > H_h^T$. This may indicate the presence of long-term memory or persistence in the series. In the context of environmental pollution, this may mean that high levels of pollution tend to remain high for a long time or to rebound after periods of decline. The trend in pollution levels continues. In terms of forecasting, the higher the value of the Hurst index, the more likely it is that the current trend will continue, $H\left(Q^h\right) \leq 1$. Moreover H^T is the theoretical threshold value for identifying the boundary between random and persistent series, $H_h^T \approx 0,54$ and is determined by the number of levels of the series that are analyzed by the formula [105, 106]:

$$H_h^T = \frac{\Gamma\left(\frac{h-1}{2}\right)}{\Gamma\left(\frac{h}{2}\right)} \cdot \frac{1}{\sqrt{\pi}} \sum_{i=1}^{h-1} \sqrt{\frac{h-i}{i}} \tag{2.24}$$

or

$$H_h^T = \sqrt{\frac{2}{\pi\left(h-1\right)}} \sum_{i=1}^{h-1} \sqrt{\frac{h-i}{i}} \tag{2.25}$$

2. If the value of the Hurst index is close to 0.5, i.e. $H\left(Q^h\right) \in \left[\frac{1}{2}, H_h^T\right]$, it means that the time series is random. In the context of time series of environmental pollution parameters, this may mean that the level of pollution in each area is very unstable and is caused by pollutant emissions in an irregular manner in different concentrations, which is not regulated. Alternatively, it may mean a state of emergency or accident if the series has previously had a clearly defined upward or downward trend.

3. If $H\left(Q^h\right) \in \left[0, \frac{1}{2}\right)$, the time series is ergodic. In the context of environmental pollution, this can mean that pollution tends to temporarily decrease after certain peaks or high values. And in general, such a time series changes faster than a random series. This may mean that there is an emergency situation with the level of pollution in the region.

The construction of the Hurst index for the time series of environmental pollution parameters in the dynamics allows you to see how the structure of the pollution level series in the region is changing and quickly respond to possible deviations from thresholds. This is very important for a monitoring system. For example, if we break down the time series

$$Q = \left(q\left(t_1\right), q\left(t_2\right), \ldots, q\left(t_n\right)\right) \tag{2.26}$$

to a sequence of time series:

$$Q = \left(Q^{1,w}, Q^{2,w+1}, \ldots, Q^{n-w+1,n}\right),\ w < n, \tag{2.27}$$

where

$$Q^{1,w} = \left(q\left(t_1\right), q\left(t_2\right), \ldots, q\left(t_w\right)\right), \tag{2.28}$$

$$Q^{2,w+1} = \left(q\left(t_2\right), q\left(t_3\right), \ldots, q\left(t_{w+1}\right)\right), \tag{2.29}$$

$$\ldots$$

$$Q^{n-w+1,n} = \left(q\left(t_{n-w+1}\right), q\left(t_{n-w+2}\right), \ldots, q\left(t_n\right)\right), \tag{2.30}$$

then it is possible to construct a time series of Hurst indices for

$$Q = \left(Q^{1,w}, Q^{2,w+1}, \ldots, Q^{n-w+1,n}\right): \tag{2.31}$$

$$H\left(Q\right) = \left(H\left(Q^{1,w}\right), H\left(Q^{2,w+1}\right), \ldots, H\left(Q^{n-w+1,n}\right)\right). \tag{2.32}$$

Then, if such a time series changes above the level of, then most likely the situation with pollution is stable, that is, either a decrease in the level of pollution or an increase is recorded, but the situation is predictable (Fig. 2.1). To predict the level of pollution, methods that have a strong trend component should be chosen. This is important for the effective construction of an environmental monitoring system. If the values of such a time series change below the level of, this may indicate an emergency or that the pollution level is changing unstably (Fig. 2.2). When predicting the pollution level, models that consider a strong random component should be chosen.

Also, if the time series values were initially above the threshold value H_h^T and then began to decline sharply and fell below this level, this may mean an increased influence of random factors on the process under consideration. In this case, you need to analyze the value of the V statistic and ensure there was indeed a loss of long-term memory in the time series. This, in turn, means possible emission emergencies that need to be addressed promptly. Figure 2.3 shows such a case when the value of the Hurst index decreases sharply, crossing the threshold level. All other cases that may occur in the case of time series analysis

$$H(Q) = \left(H\left(Q^{1,w}\right), H\left(Q^{2,w+1}\right), \ldots, H\left(Q^{n-w+1,n}\right)\right) \tag{2.33}$$

should be analyzed separately.

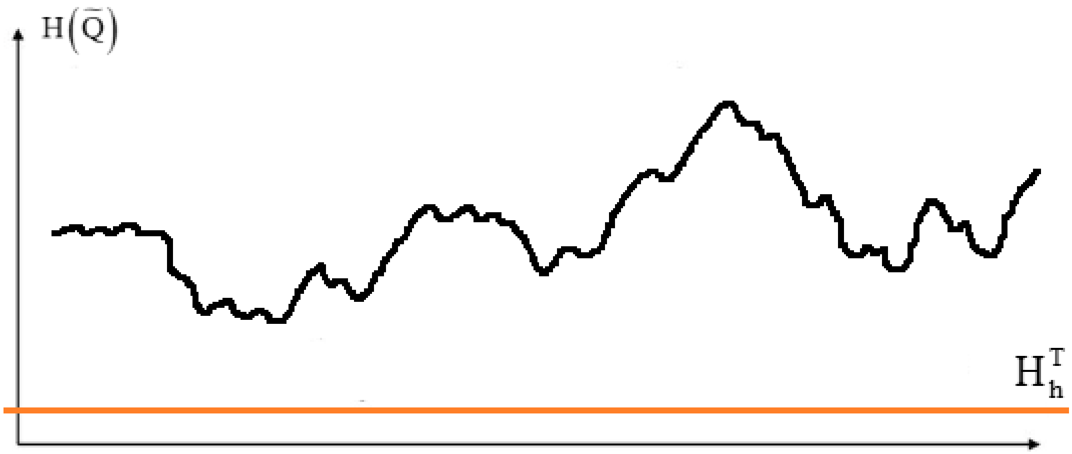


Figure 2.1. The position of the time series $H(Q)$ is above the threshold value H_h^T.

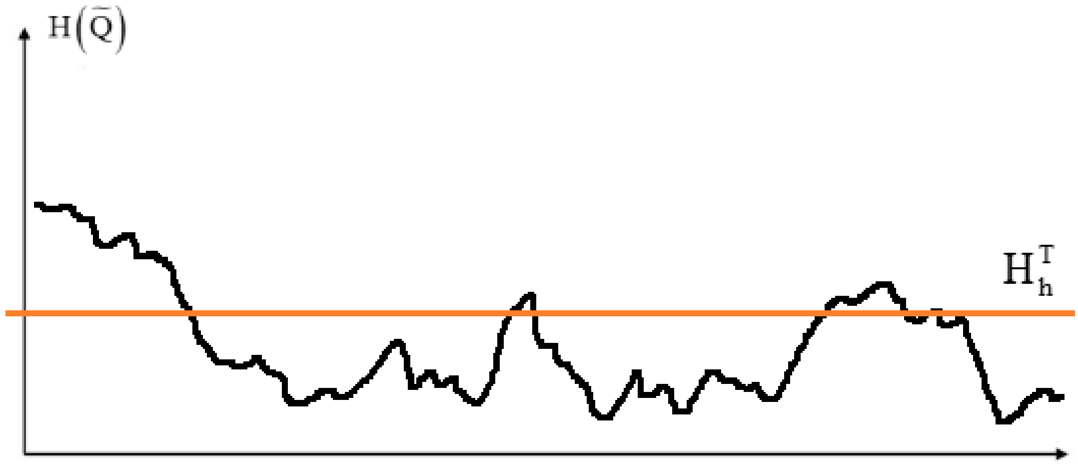


Figure 2.2. The position of the time series $H(Q)$ is below the threshold value H_h^T.

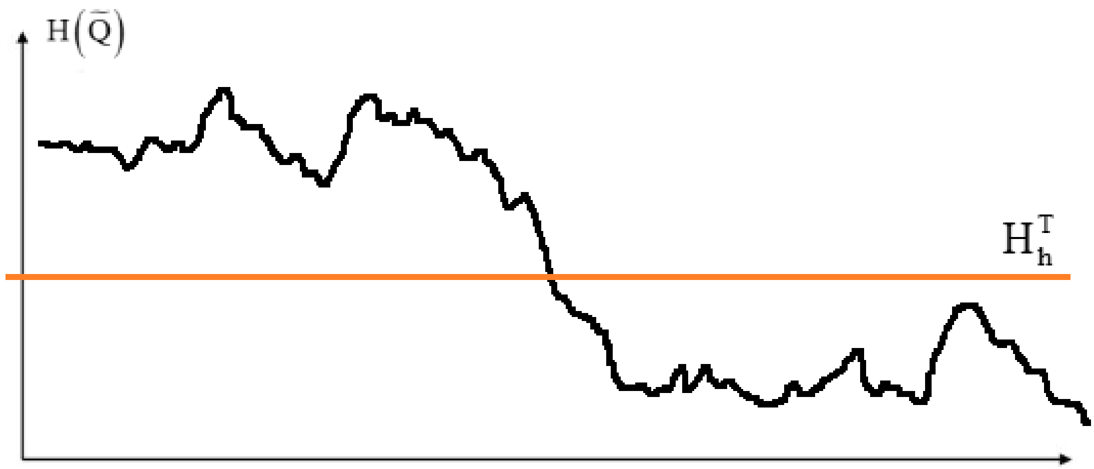


Figure 2.3. The position of the time series $H(Q)$ decreases sharply from above the threshold H_h^T to below the threshold H_h^T.

The fractal analysis of the time series of environmental pollution parameters provides critical statistical estimates that can help build forecasting models and create an effective environmental monitoring system.

2.3. Integrated model for forecasting time series of environmental pollution parameters

In this paragraph, we will consider a comprehensive model for forecasting time series of environmental pollution parameters, considering the aggregation of various forecasting models formed based on predictive statistical analysis of pollution indicators. The key feature of the model is that it combines other well-known forecasting models and allows you to adjust the parameters to correspond to the results of the predictive analysis of series based on fractal analysis.

The task is to use a time series

$$Q=\left(q\left(t_1\right),q\left(t_2\right),\ldots,q\left(t_n\right)\right) \tag{2.34}$$

to make the most accurate forecast, i.e. to establish the behavior of the time series of pollution parameters for a certain number of points ahead, i.e. to find estimates of values

$$\hat{q}\left(t_{n+1}\right),\hat{q}\left(t_{n+2}\right),\ldots,\hat{q}\left(t_{n+k}\right), \tag{2.35}$$

where $\hat{q}\left(t_{n+i}\right)$ - time series forecast $Q=\left(q\left(t_1\right),q\left(t_2\right),\ldots,q\left(t_n\right)\right)$, $i=\overline{1,k}$.

To find a solution to the problem, it is necessary to find a functional dependence that would approximate the required predicted value based on the known values of the time series. That is.

$$\hat{q}\left(t_{n+1}\right)=\Phi\left(q\left(t_c\right),q\left(t_{c+1}\right),\ldots,q\left(t_n\right)\right),\ c<n, \tag{2.36}$$

$$\hat{q}\left(t_{n+2}\right)=\Phi\left(q\left(t_{c+1}\right),q\left(t_{c+2}\right),\ldots,q\left(t_n\right),\hat{q}\left(t_{n+1}\right)\right), \tag{2.37}$$

$$\ldots$$

$$\hat{q}\left(t_{n+k}\right)=\Phi\left(q\left(t_{c+k-1}\right),q\left(t_{c+k}\right),\ldots,q\left(t_n\right),\hat{q}\left(t_{n+1}\right),\ldots,\hat{q}\left(t_{n+k-1}\right)\right). \tag{2.38}$$

To assess the quality of a forecast, you can use the average absolute error, average relative error, standard deviation, etc.

Let a set of models be given $\Phi_1,\Phi_2,\ldots,\Phi_M$, which, based on the time series Q allow you to make the most accurate forecast, i.e. find the value:

$$\hat{q}_j\left(t_{n+1}\right)=\Phi_j\left(\alpha_1^j,\alpha_2^j\ldots\alpha_m^j,q\left(t_c\right),q\left(t_{c+1}\right),\ldots,q\left(t_n\right)\right),\ c<n, \tag{2.39}$$

$$\hat{q}_j\left(t_{n+2}\right)=\Phi_j\left(\alpha_1^j,\alpha_2^j\ldots\alpha_m^j,q\left(t_{c+1}\right),q\left(t_{c+2}\right),\ldots,q\left(t_n\right),q\left(t_{n+1}\right)\right), \tag{2.40}$$

$$\ldots$$

$$\hat{q}_j\left(t_{n+k}\right)=\Phi_j\left(\alpha_1^j,\alpha_2^j\ldots\alpha_m^j,q\left(t_{c+k-1}\right),q\left(t_{c+k}\right),\ldots,q\left(t_n\right),q\left(t_{n+1}\right),\ldots,\hat{q}\left(t_{n+k-1}\right)\right),$$

$$j=\overline{1,M}, \tag{2.41}$$

where $\hat{q}_j\left(t_{n+i}\right)$ - time series forecast Q, $i=\overline{1,k}$ based on the model $j=\overline{1,M}$, α_d^j - parameters of the forecasting model j, $d=\overline{1,m}$, m – number of parameters of the forecasting model j.

Let the model Φ_1 is represented by the usual exponential model of order $p\geq 0$. Exponential order model $p\geq 0$ is determined by the formula:

$$x_n^{[p]}=\alpha\cdot x_n^{[p-1]}+\left(1-\alpha\right)x_{n-1}^{[p]}, \tag{2.42}$$

where $x_n^{[0]}=q\left(t_1\right)$, $x_0,x_0^{[2]},\ldots$ – initial conditions of exponential averages of the corresponding order [107], $\hat{q}_j\left(t_{n+1}\right)=x_n^{[p]}$, $\alpha\in\left[0,1\right]$. That is, this model will be defined as $\Phi_1\left(\alpha,q\left(t_1\right),q\left(t_2\right),\ldots,q\left(t_n\right)\right)$.

Let the model Φ_2 is represented by the Holt exponential smoothing model, which is used to model time series with a pronounced trend component [108]:

$$\hat{q}_2\left(t_{n+1}\right)=x_n+y_n, \tag{2.43}$$

$$x_n=\alpha_1 q\left(t_n\right)+\left(1-\alpha_1\right)\left(x_{n-1}+y_{n-1}\right), \tag{2.44}$$

$$y_n=\alpha_2\left(x_n-x_{n-1}\right)+\left(1-\alpha_2\right)y_{n-1}, \tag{2.45}$$

$\hat{q}_2\left(t_{n+1}\right)$ - a forecast calculated one point ahead using the Holt time series model Q, $\alpha_1,\alpha_2\in\left[0,1\right]$, accordingly, the model has the form $\Phi_2\left(\alpha_1,\alpha_2,q\left(t_1\right),q\left(t_2\right),\ldots,q\left(t_n\right)\right)$.

The Winters model Φ_3 is used for processes with an additive trend component and multiplicative seasonality. In this model, the value of the time series without a seasonal component, the trend, and the seasonal component are smoothed separately [109]:

$$\hat{q}_3(t_{n+1}) = (x_n + y_n)s_{n-P+1}, \tag{2.46}$$

$$x_n = \alpha_1 \frac{q(t_n)}{s_{n-P}} + (1-\alpha_1)(x_{n-1} + y_{n-1}), \tag{2.47}$$

$$y_n = \alpha_2 (x_n - x_{n-1}) + (1-\alpha_2) y_{n-1}, \tag{2.48}$$

$$s_n = \alpha_3 \frac{q(t_n)}{s_n} + (1-\alpha_3)s_{n-P}, \tag{2.49}$$

where $\alpha_1, \alpha_2, \alpha_3 \in [0,1]$ - smoothing parameters, P - seasonal cycle period, s_n - assessment of the seasonal component of the model. This model is denoted by $\Phi_3(\alpha_1, \alpha_2, \alpha_3, q(t_1), q(t_2), \ldots, q(t_n))$

Autoregressive model Φ_4 is determined by the formula:

$$\hat{q}(t_{n+1}) = \gamma_0 + \gamma_1 q(t_{n-1}) + \gamma_2 q(t_{n-2}) + \ldots + \gamma_c q(t_{n-c}), \tag{2.50}$$

the parameters are not determined in advance and are calculated based on the condition of minimizing the sum of the mean square errors. The number of points to use the autoregressive model depends on the memory capacity, so we can write the model as $\Phi_4(q(t_{n-c+1}), q(t_{n-c+2}), \ldots, q(t_n))$

The moving average model is defined by a parameter that determines the number of points used to calculate the forecast value. The larger the memory in the time series, the larger this parameter should be. That is, the model $\Phi_5(q(t_{n-c+1}), q(t_{n-c+2}), \ldots, q(t_n))$ is defined as follows:

$$\hat{q}(t_{n+1}) = \frac{1}{\alpha} \sum_{j=0}^{c-1} q(t_{n-j}), \ \alpha > 0. \tag{2.51}$$

Weighted moving average with a set of normalized weights $\{\omega_1, \omega_2, \dots, \omega_c\}$, $\sum_{j=1}^{c} \omega_j = 1$, is determined by the formula:

$$\hat{q}(t_{n+1}) = \frac{1}{c} \sum_{j=0}^{c-1} \omega_{j+1} q(t_{n-j}), \; c > 0. \tag{2.52}$$

This model is denoted by $\Phi_6(q(t_{n-c+1}), q(t_{n-c+2}), \dots, q(t_n))$. The number of models can be increased. However, it should be noted that the initial parameters should be chosen considering the results of the pre-prognostic analysis. This way, it will be possible to obtain a smaller time series forecasting error and make a more accurate forecast of the time series of environmental pollution parameters. This is very important for building an effective environmental monitoring system.

Let's build a general forecasting model that would take into account all the models described above, as well as the results of the pre-prognostic fractal analysis of the time series. The model differs from the known models by providing the ability to adapt model parameters to changes in the environment. Each model described generates an error when applied. The accuracy of the model is determined by the minimum forecasting error. Let the time series plot $Q^o = (q(t_z), q(t_{z+1}), \dots, q(t_n))$ the accuracy of the forecasting models is monitored, then the error can be calculated for each model $G_n^i(Q^o, Q)$ by the formula:

$$G_n^i(Q^o, Q) = \sqrt{\frac{1}{n - z + 1} \sum_{j=z}^{n} \left(\hat{q}_i(t_j) - q_i(t_j)\right)^2}, \; i = \overline{1,6}, \tag{2.53}$$

$G_n^i(Q^o, Q)$ - prediction error of point $q(t_n)$, based on the model Φ_i.

For each model, we calculate the criterion for selecting a model to perform the forecast using the formula:

$$\overset{i}{G}_n = \eta G_n^i(Q^o, Q) + (1 - \eta) \overset{i}{G}_{n-1}, \; \eta \in [0,1], \tag{2.54}$$

where G_n^i - exponentially smoothed point prediction error $q(t_n)$, based on the model Φ_i.

If the error argument is the model on which it was calculated, i.e. $G_n^i = G_n(\Phi_i)$. Then, the model for which the condition of minimum forecasting error is met is selected to perform the forecast:

$$\Phi_i^* = \arg\min_i \left(G_n^i\right). \qquad (2.55)$$

For the selected list of models, we will use their connection with the results of the pre-forecast analysis. That is, with the calculated value of $H(Q^n)$.

For the first model, since the smoothing parameter indicates the weight of the influence of previous values of the series on the result. Moreover, if the value is close to one, then the forecast by this model will resemble a naive one. On the other hand, a forecast may be naive if the series being forecasted is highly persistent. That is, a rational formula can be derived to determine the smoothing parameter in the model $\Phi_1(\alpha, q(t_1), q(t_2), \ldots, q(t_n))$:

$$\alpha = \begin{cases} H(Q^n), H(Q^n) \geq 0,5 \\ 0.5, H(Q^n) < 0,5 \end{cases}. \qquad (2.56)$$

In the second model $\Phi_2(\alpha_1, \alpha_2, q(t_1), q(t_2), \ldots, q(t_n))$ first smoothing parameter α_1 - determines the trend, and the second α_2 - the random component. Accordingly, these parameters can be determined by the formula:

$$\alpha_1 = \begin{cases} H(Q^n), H(Q^n) \geq 0,5 \\ 0.5, H(Q^n) < 0,5 \end{cases}, \qquad (2.57)$$

$$\alpha_2 = \begin{cases} \max\left\{1, 0.5 + 10\left|H_h^T - H(Q^n)\right|\right\}, 0.5 \leq H(Q^n) \leq H_h^T \\ 0.5, H(Q^n) > H_h^T \text{ or } H(Q^n) < 0.5 \end{cases}. \qquad (2.58)$$

In the third model $\Phi_3\left(\alpha_1,\alpha_2,\alpha_3,q\left(t_1\right),q\left(t_2\right),\ldots,q\left(t_n\right)\right)$ first smoothing parameter α_1 - determines the trend, and the second α_2 - random component, the third - α_3 - seasonality. If the points of change in the trend of the curve V of the statistics correspond to the seasonality P, then these parameters can be determined by the formula:

$$\alpha_1,\alpha_3=\begin{cases}H\left(Q^n\right),H\left(Q^n\right)\geq 0,5\\ 0.5,H\left(Q^n\right)<0,5\end{cases}, \tag{2.59}$$

$$\alpha_2=\begin{cases}\max\left\{1,0.5+10\left|H_h^T-H\left(Q^n\right)\right|\right\},0.5\leq H\left(Q^n\right)\leq H_h^T\\ 0.5,H\left(Q^n\right)>H_h^T \text{ or } H\left(Q^n\right)<0.5\end{cases}. \tag{2.60}$$

In the models $\Phi_4\left(q\left(t_{n-c+1}\right),q\left(t_{n-c+2}\right),\ldots,q\left(t_n\right)\right)$, $\Phi_5\left(q\left(t_{n-c+1}\right),q\left(t_{n-c+2}\right),\ldots,q\left(t_n\right)\right)$ and $\Phi_6\left(q\left(t_{n-c+1}\right),q\left(t_{n-c+2}\right),\ldots,q\left(t_n\right)\right)$ the value of the parameter is determined by the presence of long-term memory in the time series. It can be determined by visual inspection of the V statistics curve. If the point that shows a sharp change in the upward and downward trend of this curve is equal to P, $P\in\mathbb{N}$, then the parameter c can be set to P, i.e., models of this form will be built:

$$\Phi_t\left(q\left(t_{n-P+1}\right),q\left(t_{n-P+2}\right),\ldots,q\left(t_n\right)\right),\ t=\overline{4,6}. \tag{2.61}$$

The peculiarity of this model is that, in addition to considering the results of the predictive fractal analysis, it is adaptive. That is, it could adapt the model parameters to changes in the environment, which is especially important when using such models in environmental monitoring systems.

Conclusions to chapter 2

1. The comprehensive model for forecasting time series of environmental pollution indicators was described, considering the aggregation of various forecasting models formed based on a predictive statistical analysis of pollution indicators and having an adaptive nature. The model differs from the

known models by providing the ability to adapt the model parameters to changes in the state of the environment, which is especially important when using such models in environmental monitoring systems.

2. The fractal analysis method of time series is described, which allows the finding of the Hurst index for its use in the developed forecasting models and allows the determining the presence of long-term memory, cyclicity, etc., in the time series.
3. The complex forecasting model includes higher-order exponential smoothing models, Holt, Winters, moving average, weighted moving average, and autoregressive models. All the parameters set in these models are related to the Hurst index, which is calculated based on the predictive fractal statistical analysis of the time series. Relevant descriptions and justifications are given.
4. It is indicated that using such a model as part of an economic modeling system will help to more effectively predict and respond to possible changes in the values of pollution parameters. In particular, the persistence of the time series of pollution parameters may mean a stable upward or downward trend in pollution. Suppose the time series becomes close to random or ergodic. In that case, this may mean an emergency or that additional non-permanent emissions have appeared in the region that need to be monitored.

CHAPTER 3. MONITORING OF ENVIRONMENTAL POLLUTION PARAMETERS FOR ENVIRONMENTAL SAFETY MANAGEMENT

3.1. Method for monitoring environmental pollution parameters

In this paragraph, we will consider a method of monitoring environmental pollution parameters based on a comprehensive model for predicting the time course of pollution parameters. The use of the model is important because it allows us to predict how the process will change in the future and adjust the current assessment. It is also important for the method to qualitatively record the values of pollution parameters using appropriate sensors. Understanding the structure of the time series of pollution parameters, which can be calculated based on fractal analysis, allows us to predict possible harbingers of a sharp change in the trend, which may indicate unauthorized emissions, i.e., the emergence of new pollutants or an emergency. This is very important for high-quality environmental monitoring.

Let us consider the first significant step before applying the environmental monitoring method: collecting data on the state of the environment and its parameters, taking into account various pollutants. Environmental pollution parameters can be measured using different types of sensors designed specifically to detect various pollutants in the air, water, soil, or other parts of the environment. Here is a general description of the process of measuring pollution parameters using sensors:

1. Select the type of sensors. First, you need to determine which pollution parameters you want to measure. For example, this can be the concentration level of various gases (e.g., nitrogen, sulfur, carbon oxides), air pollution (PM2.5, PM10), dissolved solids in water, moisture level, temperature, pressure, and other parameters.

2. Selecting sensors. After defining the parameters, you need to select the appropriate sensors that are capable of measuring these parameters. Different types of sensors, such as electrochemical, optical, gravity, thermal, etc., are designed to measure different substances and parameters.

3. Installation of sensors. Sensors are placed in the right places to measure pollution parameters. For example, sensors can be placed on poles, industrial areas, near roads, or other strategic locations to measure air quality.

4. Data collection. Sensors continuously collect data on the values of pollution parameters in real-time. This data can be stored on-site or transmitted directly to a centralized data collection system.

5. Data analysis. The data obtained is analyzed to determine the pollution level and identify possible sources of pollution. This may include comparing values with norms and standards, looking for trends and patterns of change, and determining the impact of pollution on the environment and human health.

6. Data visualization. The analysis results can be visualized through graphs, charts, maps, or other visual aids to understand and perceive information better.

7. Communication of results. The measurements and analysis results can be made public and shared with interested stakeholders, including government agencies, NGOs, residents, etc., to take appropriate measures to reduce pollution and improve environmental quality.

This is only a general description of measuring environmental pollution parameters using sensors. Each specific case may have its peculiarities, depending on the type of sensors, the parameters to be measured, and the specifics of the environment. This paper pays less attention to the technical component of measuring pollution using sensors. The main task is to develop information technology, i.e. appropriate methods, models and tools that would allow to assess the state of the environment and predict its change in the future, i.e. to conduct monitoring.

Also, if monitoring is required at critical infrastructure facilities to ensure safety, then appropriate sensors must be selected for each such facility, and a system for monitoring and assessing the state of the environment must be set up. For example, in a subway tunnel, it is necessary to monitor the level of air pollution, the presence of smoke, and sufficient oxygen in the air. If there is a deviation from the required standards, appropriate measures must be taken immediately. This is important because it can affect people's lives and health. The sensor system is similarly modified for other critical infrastructure facilities, such as airports, power plants, factories, etc.

Let's consider the following steps of the method that relate directly to monitoring. Let's assume that based on the time series

$$Q=\left(q\left(t_1\right),q\left(t_2\right),\ldots,q\left(t_n\right)\right) \tag{3.1}$$

a forecast was made, i.e., the behavior of the time series of pollution parameters for a certain number of points ahead was determined, i.e., estimates of the values were found

$$\hat{q}\left(t_{n+1}\right),\hat{q}\left(t_{n+2}\right),\ldots,\hat{q}\left(t_{n+k}\right), \tag{3.2}$$

for example, based on the comprehensive model for predicting pollution parameters described in the previous section.

First, to implement this forecasting model, it is necessary to implement the statistical fractal analysis described in Section 2. That is, to find the value of the Hurst index and the function V of the statistics and other necessary indicators. After that, based on the results of the statistical fractal analysis, a comprehensive model for predicting a time series of pollution parameters with a particular horizon can be implemented. The horizon can generally be determined by the amount of long-term memory identified in the time series based on fractal analysis. However, a forecast with a horizon of 5 will be sufficient to implement this method.

That is, let's say that based on the time series $Q=\left(q\left(t_1\right),q\left(t_2\right),\ldots,q\left(t_n\right)\right)$ Hurst's index is calculated $H\left(Q^h\right)$, V statistics and theoretical indicator of the limit of the level of randomness for the input time series H_h^T. Also, Hurst's indices should be calculated for a family of time series that are formed on the basis of the input time series using the rolling window method by shifting and fixing the formed time series. The result is a time series:

$$H\left(Q\right)=\left(H\left(Q^{1,w}\right),H\left(Q^{2,w+1}\right),\ldots,H\left(Q^{n-w+1,n}\right)\right). \tag{3.3}$$

Next, you need to implement a comprehensive forecasting model with a forecast with a horizon of 5. After that, you need to interpret the monitoring results. It consists of three steps:

The first step is to find a trend. Let the current observation point be the point $q(t_n)$. Let's find the average of the last points of the time series of the environmental pollution parameter. You can set $r = 5$. That is

$$q_n^- = \frac{1}{r}\sum_{i=0}^{r-1} q(t_{n-i}), \tag{3.4}$$

where q_n^- - is the average value of the last r points of the time series $Q = (q(t_1), q(t_2), \ldots, q(t_n))$, including the current observation point.

We will also find the average value of the forecasts calculated on the basis of a comprehensive forecasting model, taking into account the results of fractal analysis of the time series:

$$q_n^+ = \frac{1}{r}\sum_{i=1}^{r} q(t_{n+i}), \tag{3.5}$$

where q_n^+ - is the average value of the last r points of the time series $Q = (q(t_1), q(t_2), \ldots, q(t_n))$, not including the current observation point.

Then

$$R_n = \frac{q_n^+}{q_n^-}, \tag{3.6}$$

$$\operatorname{sgn}(R_n - 1) = \begin{cases} 1, R_n - 1 > 0 \\ 0, R_n - 1 = 0 \\ -1, R_n - 1 < 0 \end{cases}. \tag{3.7}$$

Then you can determine how the current average differs from the forecast average. That is:

- if $\operatorname{sgn}(R_n - 1) = 1$, then the increase is positive;
- if $\operatorname{sgn}(R_n - 1) = -1$, then the increase is negative;
- if $\operatorname{sgn}(R_n - 1) = 0$, there is no growth.

The amount of the increase is determined by the formula:

$$\overline{R}_n = \frac{\left|q_n^+ - q_n^-\right| \cdot 100\%}{q_n^-}. \tag{3.8}$$

It can also be established that the more persistent the time series of pollution parameters is, the more reliable the indicator of the magnitude of the increase is, i.e., the reliability will be determined by the results of the assessment $H\left(Q^h\right)$. If:

- $H\left(Q^h\right) < H_h^T$, reliability is very low;
- $H_h^T \le H\left(Q^h\right) \le 0.6$, reliability is low;
- $0.6 < H\left(Q^h\right) \le 0.8$, the reliability is average;
- $0.8 < H\left(Q^h\right) \le 1$, reliability is high.

If the V statistic indicates a cycle size greater than 10, this indicates a long-term memory in the time series of its initial conditions. This correspondingly increases the reliability of the time series trend forecast and can be used by environmental monitoring systems. The cycle length is defined as the projection of the point on the V statistic curve where the trend abruptly changes onto the abscissa axis. The following rule can be formulated: if the average cycle length c, determined from the V statistic:

- $c < 5$, the memory is short-term and the reliability of calculating the trend direction is low;
- $5 \le c \le 10$, the memory is medium-term and the reliability of trend direction calculation is average;
- $c > 10$, the memory is long-term and the reliability of trend direction calculation is high.

So, the method of monitoring environmental pollution parameters has the following steps:

1. Building a time series of environmental pollution parameters $Q = \left(q\left(t_1\right), q\left(t_2\right), \ldots, q\left(t_n\right)\right)$. In this case, you need to configure the correct collection

of pollution information using the appropriate sensors installed in the appropriate location. It should be noted that different types of sensors can be used for different types of pollutants. For the developed method, the order of values or levels of the time series, as well as the content of pollutants, are not important. The results are interpreted by the person responsible for reporting on environmental pollution monitoring.

2. Conducting a fractal statistical analysis on this time series, i.e. finding the value of the Hurst index $H\left(Q^{h}\right)$, as well as functions of V statistics and other necessary indicators. The minimum number of time series members to implement this method should be more than 500 points. This is an empirical criterion that must be met to correctly calculate the parameters of fractal analysis. Also, the fractal analysis should be used to calculate the time series of Hearst indicators for the series formed from the input series using the rolling window method $H\left(Q\right)=\left(H\left(Q^{1,w}\right),H\left(Q^{2,w+1}\right),\ldots,H\left(Q^{n-w+1,n}\right)\right)$.

3. The next step is to implement a model or models for forecasting time series of environmental pollution parameters. In this method, it is proposed to use a comprehensive forecasting model taking into account the results of statistical fractal analysis.

4. Calculation of the growth rate or trend direction based on a comprehensive forecasting model taking into account the results of statistical fractal analysis. Reliability of the trend direction calculation is determined based on the results of calculating the Hurst's index for the input time series and the quasi-cycle value using the V statistics method.

5. The next step is to formulate a comprehensive environmental assessment and make decisions on improving the environmental situation in the respective region, including a set of appropriate measures.

Depending on the critical infrastructure facility where the method of monitoring pollution parameters is implemented, it is necessary to select which parameters to monitor accordingly. Accordingly, the described thresholds need to be adjusted. However, the described method is generally universal. Depending on the critical infrastructure facility and specific environmental pollution parameters, these values are determined based on the results of previous observations.

3.2. Model of environmental assessment in the monitoring system

Since several indicators need to be considered to assess the environment's state, such a task can be formulated as a multi-criteria optimization problem. In paragraph 3.1, we have developed the indicators used in the environmental monitoring method.

After predicting the time series of environmental pollution parameters, the magnitude of the increase and the direction of the trend are formulated: $\operatorname{sgn}(R_n - 1)$ та $\overline{R}_n$. Also, based on the results of the statistical fractal analysis of the time series, the V statistic, the average value of the time series cycle, and Hurst's index were determined. Considering the empirical analysis of these indicators, the intervals in which these values should fall were formed to achieve the best environmental safety. Such formulations are essential for managing the environmental situation in the region.

Accordingly, if $Q^n \in X$:

$$g_1(Q^n) = -\overline{R}_n \cdot \operatorname{sgn}(R_n - 1), \tag{3.9}$$

$g_1(Q^n)$ - is an incremental function,

$$g_2(Q^n) = c(Q^n), \tag{3.10}$$

$g_2(Q^n)$ - cyclical function,

$$g_3(Q^n) = H(Q^n), \tag{3.11}$$

$g_3(Q^n)$ - trend resistance function,

we have a maximization problem:

$$\max\left\{g_1\left(Q^n\right), g_2\left(Q^n\right), g_3\left(Q^n\right)\right\}, \tag{3.12}$$

$$g_j\left(Q^n\right): \mathbb{R}^n \to \mathbb{R},\ j=\overline{1,3}. \tag{3.13}$$

The ideal point would be

$$y^A = \left(y_1^A, y_2^A, y_3^A\right) \tag{3.14}$$

and

$$y_j^A = \max_{Q^n \in X} g_j\left(Q^n\right),\ j=\overline{1,3}. \tag{3.15}$$

Finding the ideal point in a multi-criteria maximization problem means finding a set of criteria values for which no other solution is better than this one for all criteria simultaneously. This point is sometimes called the "Pareto-optimal" point. The main steps in conceptually finding a solution to a multi-criteria maximization problem include:

1. First, it is necessary to clearly define all the criteria by which the solution is evaluated. This can be, for example, profit maximization, cost minimization, efficiency maximization, etc.

2. Using optimization and data analysis methods, building a Pareto set consisting of all possible solutions that all criteria cannot improve simultaneously is necessary. This may require a large number of calculations and the use of specialized optimization algorithms.

3. Selecting the ideal point. The ideal point in the Pareto set is the one that maximizes (or minimizes) the value of each criterion simultaneously. This point can be selected as the solution to the maximization problem.

4. Checking the efficiency. After selecting the ideal point, it is essential to verify its effectiveness by all the criteria. This may involve running simulations or analyzing the results to ensure the selected solution is optimal for all relevant criteria.

5. In some cases, it may be necessary to find solutions outside the Pareto set, making trade-offs between different criteria. In such cases, it is important to determine the ideal point based on reasonable solutions.

In general, the conceptual solution of a multi-criteria maximization problem requires a balance between different criteria and effective optimization methods to find optimal solutions. The described maximization model allows for achieving the required level of environmental certainty and can be used to monitor environmental pollution parameters.

3.3. Development of an environmental assessment index for managing critical infrastructure facilities

In order to assess the state of the environment based on the method of assessing environmental pollution parameters, an index needs to be developed. This index considers the results of fractal analysis of the time series, time series forecasting, etc. To do this, we will introduce a scale with four letter grades formed based on previous calculations. The rating scale is shown in Tables 3.1 through 3.6.

The scale for assessing the ecological state of the environment is two-level. The Latin letters A, B, C, D, E, F define the first level. The letter A is considered to be the highest score, and F is considered to be the lowest. The grades are determined by forecasting the trend of pollution parameters based on the developed comprehensive model. A mark is added to these letters at the second level: "---", "--", "-", "+", "++", "+++" or no mark is added. Thus, the six-point system is transformed into a 70-point system. A mark containing "pluses" increases the grade, a mark containing "minuses" decreases the grade. The absence of a mark does not change the grade.

It should be noted that for certain critical infrastructure facilities where such environmental assessment and monitoring systems are implemented: air, water, soil, etc., the relevant thresholds may be specified. This can be done based on preliminary observation and analysis of statistical indicators. The following scales apply to different pollutants and can be used in general regardless of the analyzed pollution parameters.

Table 3.1. Scale of the environmental assessment index for assessing the environmental condition of the environment for A

№	Description				Assesment
	R_n	$\text{sgn}(R_n - 1)$	$H(Q^n)$	$c(Q^n)$	
1	$> 4\%$	-1	$(0.75, 1]$	$c > 10$	A^{+++}
2	$> 4\%$	-1	$(0.75, 1]$	$5 \le c \le 10$	A^{++}
3	$> 4\%$	-1	$(H_n^T, 0.75]$	$c > 10$	
4	$> 4\%$	-1	$(0.75, 1]$	$c < 5$	A^{+}
5	$> 4\%$	-1	$(H_n^T, 0.75]$	$5 \le c \le 10$	
6	$> 4\%$	-1	$(H_n^T, 0.75]$	$c < 5$	A
7	$> 4\%$	-1	$(0.5, H_n^T]$	$c > 10$	
8	$> 4\%$	-1	$(0.5, H_n^T]$	$5 \le c \le 10$	A^{-}
9	$> 4\%$	-1	$[0, 0.5]$	$c > 10$	
10	$> 4\%$	-1	$(0.5, H_n^T]$	$c < 5$	A^{--}
11	$> 4\%$	-1	$[0, 0.5]$	$5 \le c \le 10$	
12	$> 4\%$	-1	$[0, 0.5]$	$c < 5$	A^{---}

Table 3.2. Scale of the environmental assessment index for assessing the environmental condition of the environment for B

№	Description				Assesment
	R_n	$\text{sgn}(R_n - 1)$	$H(Q^n)$	$c(Q^n)$	
1	$(2, 4]$	-1, 0	$(0.75, 1]$	$c > 10$	B^{+++}
2	$(2, 4]$	-1, 0	$(0.75, 1]$	$5 \le c \le 10$	

3	$(2,4]$	-1, 0	$(H_n^T,0.75]$	$c>10$	B^{++}
4	$(2,4]$	-1, 0	$(0.75,1]$	$c<5$	B^{+}
5	$(2,4]$	-1, 0	$(H_n^T,0.75]$	$5\le c\le 10$	
6	$(2,4]$	-1, 0	$(H_n^T,0.75]$	$c<5$	B
7	$(2,4]$	-1, 0	$(0.5,H_n^T]$	$c>10$	
8	$(2,4]$	-1, 0	$(0.5,H_n^T]$	$5\le c\le 10$	B^{-}
9	$(2,4]$	-1, 0	$[0,0.5]$	$c>10$	
10	$(2,4]$	-1, 0	$(0.5,H_n^T]$	$c<5$	B^{--}
11	$(2,4]$	-1, 0	$[0,0.5]$	$5\le c\le 10$	
12	$(2,4]$	-1, 0	$[0,0.5]$	$c<5$	B^{---}

Table 3.3. Scale of the environmental assessment index for assessing the environmental condition of the environment for C

№	Description				Assesment
	R_n	$\operatorname{sgn}(R_n-1)$	$H(Q^n)$	$c(Q^n)$	
1	$(0,2]$	-1, 0	$(0.75,1]$	$c>10$	C^{+++}
2	$(0,2]$	-1, 0	$(0.75,1]$	$5\le c\le 10$	C^{++}
3	$(0,2]$	-1, 0	$(H_n^T,0.75]$	$c>10$	
4	$(0,2]$	-1, 0	$(0.75,1]$	$c<5$	C^{+}
5	$(0,2]$	-1, 0	$(H_n^T,0.75]$	$5\le c\le 10$	
6	$(0,2]$	-1, 0	$(H_n^T,0.75]$	$c<5$	C
7	$(0,2]$	-1, 0	$(0.5,H_n^T]$	$c>10$	

8	$(0,2]$	-1, 0	$(0.5, H_n^T]$	$5 \le c \le 10$	C^-
9	$(0,2]$	-1, 0	$[0, 0.5]$	$c > 10$	
10	$(0,2]$	-1, 0	$(0.5, H_n^T]$	$c < 5$	C^{--}
11	$(0,2]$	-1, 0	$[0, 0.5]$	$5 \le c \le 10$	
12	$(0,2]$	-1, 0	$[0, 0.5]$	$c < 5$	C^{---}

Table 3.4. Scale of the environmental assessment index for assessing the environmental condition of the environment for D

№	Descrition				Assesment
	R_n	$\mathrm{sgn}(R_n - 1)$	$H(Q^n)$	$c(Q^n)$	
1	$[0,2]$	1, 0	$(0.75, 1]$	$c > 10$	D^{+++}
2	$[0,2]$	1, 0	$(0.75, 1]$	$5 \le c \le 10$	D^{++}
3	$[0,2]$	1, 0	$(H_n^T, 0.75]$	$c > 10$	
4	$[0,2]$	1, 0	$(0.75, 1]$	$c < 5$	D^+
5	$[0,2]$	1, 0	$(H_n^T, 0.75]$	$5 \le c \le 10$	
6	$[0,2]$	1, 0	$(H_n^T, 0.75]$	$c < 5$	D
7	$[0,2]$	1, 0	$(0.5, H_n^T]$	$c > 10$	
8	$[0,2]$	1, 0	$(0.5, H_n^T]$	$5 \le c \le 10$	D^-
9	$[0,2]$	1, 0	$[0, 0.5]$	$c > 10$	
10	$[0,2]$	1, 0	$(0.5, H_n^T]$	$c < 5$	D^{--}
11	$[0,2]$	1, 0	$[0, 0.5]$	$5 \le c \le 10$	
12	$[0,2]$	1, 0	$[0, 0.5]$	$c < 5$	D^{---}

Table 3.5. Scale of the environmental assessment index for assessing the environmental condition of the environment for E

№	Description				Assesment
	R_n	$\mathrm{sgn}(R_n - 1)$	$H(Q^n)$	$c(Q^n)$	
1	$(2,4]$	1, 0	$(0.75,1]$	$c > 10$	E^{+++}
2	$(2,4]$	1, 0	$(0.75,1]$	$5 \le c \le 10$	E^{++}
3	$(2,4]$	1, 0	$(H_n^T, 0.75]$	$c > 10$	
4	$(2,4]$	1, 0	$(0.75,1]$	$c < 5$	E^{+}
5	$(2,4]$	1, 0	$(H_n^T, 0.75]$	$5 \le c \le 10$	
6	$(2,4]$	1, 0	$(H_n^T, 0.75]$	$c < 5$	E
7	$(2,4]$	1, 0	$(0.5, H_n^T]$	$c > 10$	
8	$(2,4]$	1, 0	$(0.5, H_n^T]$	$5 \le c \le 10$	E^{-}
9	$(2,4]$	1, 0	$[0, 0.5]$	$c > 10$	
10	$(2,4]$	1, 0	$(0.5, H_n^T]$	$c < 5$	E^{--}
11	$(2,4]$	1, 0	$[0, 0.5]$	$5 \le c \le 10$	
12	$(2,4]$	1, 0	$[0, 0.5]$	$c < 5$	E^{---}

Table 3.6. Scale of the environmental assessment index for assessing the environmental condition of the environment for F

№	Description				Assesment
	R_n	$\mathrm{sgn}(R_n - 1)$	$H(Q^n)$	$c(Q^n)$	
1	$> 4\%$	1	$(0.75,1]$	$c > 10$	F^{+++}
2	$> 4\%$	1	$(0.75,1]$	$5 \le c \le 10$	

3	$>4\%$	1	$\left(H_n^T, 0.75\right]$	$c>10$	F^{++}
4	$>4\%$	1	$\left(0.75, 1\right]$	$c<5$	F^{+}
5	$>4\%$	1	$\left(H_n^T, 0.75\right]$	$5 \le c \le 10$	
6	$>4\%$	1	$\left(H_n^T, 0.75\right]$	$c<5$	F
7	$>4\%$	1	$\left(0.5, H_n^T\right]$	$c>10$	
8	$>4\%$	1	$\left(0.5, H_n^T\right]$	$5 \le c \le 10$	F^{-}
9	$>4\%$	1	$\left[0, 0.5\right]$	$c>10$	
10	$>4\%$	1	$\left(0.5, H_n^T\right]$	$c<5$	F^{--}
11	$>4\%$	1	$\left[0, 0.5\right]$	$5 \le c \le 10$	
12	$>4\%$	1	$\left[0, 0.5\right]$	$c<5$	F^{---}

Table 3.1 describes the scale for assessing the environmental condition of the environment for the score A. Here, the value means that the increase in the pollution parameter increases by more than 4 percent, while the value of the sign of the increase $\operatorname{sgn}(R_n - 1) = -1$. That is, this increase is negative. This means that the level of pollution of this parameter is decreasing compared to the previous period. At the same time, a gradation of estimates is established for the case of different values of the Hurst index $H(Q^n)$ and average cycle time $c(Q^n)$.

If the value of the Hurst index $H(Q^n) \in (0.75, 1]$ - is the first percenter, then "++" is added to the letter grade. If $H(Q^n) \in \left(H_n^T, 0.75\right]$, i.e., the second percentile, then a "+" is added to the letter grade. If $H(Q^n) \in \left(0.5, H_n^T\right]$, i.e., the time series is random, then "-" is added to the letter grade. If $H(Q^n) \in [0, 0.5]$, i.e., the time series is random, then "--" is added to the letter score.

This sign system is also adjusted to take into account the average cycle length: if $c<5$, then "-" is added to the letter grade, if $5 \le c \le 10$, then nothing is added or subtracted from the letter grade, if $c>10$, then to the letter grade is added «+».

Table 3.2 describes the scale for assessing the environmental condition of the environment for the score B. Here, the value of $R_n \in (2,4]$, at the same time, the value of the incremental sign $\operatorname{sgn}(R_n - 1) = -1$ or $\operatorname{sgn}(R_n - 1) = 0$. That is, this increase is negative or zero. This means that the level of pollution of this parameter decreases compared to the previous period or remains constant. At the same time, a gradation of estimates is established for the case of different values of the Hurst index $H(Q^n)$ and average cycle time $c(Q^n)$ similar to the description for Table 3.1.

Table 3.3 describes the scale for assessing the environmental condition of the external environment for the C assessment. Here the values are $R_n \in (0,2]$, at the same time, the value of the incremental sign $\operatorname{sgn}(R_n - 1) = -1$ or $\operatorname{sgn}(R_n - 1) = 0$. That is, this increase is negative or zero. This means that the level of pollution of this parameter decreases compared to the previous period or remains constant. At the same time, a gradation of estimates is established for the case of different values of the Hurst index $H(Q^n)$ and average cycle time $c(Q^n)$ similar to the description for Table 3.1.

Table 3.4. describes the scale for assessing the environmental condition of the external environment for the D score. Here the values are $R_n \in [0,2]$, at the same time, the value of the incremental sign $\operatorname{sgn}(R_n - 1) = 1$ or $\operatorname{sgn}(R_n - 1) = 0$. That is, this increase is positive or zero. This means that the level of pollution of this parameter is increasing compared to the previous period or remains constant. At the same time, a gradation of estimates is established for the case of different values of the Hurst index $H(Q^n)$ and average cycle time $c(Q^n)$ similar to the description for Table 3.1.

Table 3.5 describes the scale for assessing the environmental condition of the external environment for the E assessment. Here the values are $R_n \in (2,4]$, at the same time, the value of the incremental sign $\operatorname{sgn}(R_n - 1) = 1$ or $\operatorname{sgn}(R_n - 1) = 0$. That is, this increase is positive or zero. This means that the level of pollution of this parameter is increasing compared to the previous period or remains constant. At the same time, a gradation of estimates is established for the case of different values of the Hurst index $H(Q^n)$ and average cycle time $c(Q^n)$ similar to Table 3.1.

Table 3.6 describes the scale for assessing the environmental condition of the external environment for the F score. Here the values are $R_n > 4\%$, at the same time, the value of the incremental sign: $\operatorname{sgn}(R_n - 1) = 1$ or $\operatorname{sgn}(R_n - 1) = 0$. That is, this increase is positive or zero. This means that the level of pollution of this parameter is increasing compared to the previous period or remains constant. At the same time, a gradation of estimates is established for the case of different values of the Hurst index $H(Q^n)$ and average cycle time $c(Q^n)$ similar to Table 3.1.

The described scale allows for a comprehensive approach to assessing the state of environmental pollution, as the scale contains 70 ratings from the highest "A^{+++}" to the lowest "F^{---}". The assessment considers the results of forecasting pollution parameters based on a comprehensive model with a predictive statistical fractal time series analysis.

The more persistent the time series is, i.e., the higher the value of the Hurst $H(Q^n)$ is obtained for a time series of pollution parameters, the more stable is the growth or decline in pollution levels, which confirms the hypothesis of a directed trend towards improvement or deterioration of the environmental situation. The average cycle time is also a separate indicator. The higher the value of the average cycle time $c(Q^n)$, the longer the memory of the time series of its initial conditions and, accordingly, the more stable the statement about the growth or decline of the level of pollution. The letter score is formed taking into account the values of the trend increment and the sign of the increment, which are calculated on the basis of a complex model for predicting the time series of pollution parameters.

The verbal assessment states that a high score means a steady downward trend in the region's pollution level, and a low score means a steady upward trend in the pollution level. The resulting scale defines a new vision of the procedure for assessing the state of environmental pollution, considering the new concept of assessing, forecasting, and monitoring time series of pollution parameters based on a comprehensive trend forecasting model with statistical fractal analysis of time series.

The Environmental Assessment Index is a key tool for determining and monitoring the level of pollution and environmental threats in a particular area. It can be used to:

1. Tracking trends. The index allows you to track changes in the state of the environment over time. This allows you to monitor the development of the situation and respond to environmental threats promptly.
2. The index can be used to evaluate the effectiveness of environmental protection measures and determine whether the projected level of improvement is being achieved.
3. The index allows for comparing the state of the environment between different regions, countries, or cities, which helps to identify priority areas for action and share experiences.
4. The environmental assessment presented through the index provides essential information to the public and political decision-makers to make informed decisions and engage stakeholders in implementing environmental improvement measures.
5. The index can guide investment in environmental projects, helping investors and development organizations prioritize areas of focus.

Overall, the Environmental Performance Index is essential for ensuring sustainable development and preserving the environment for future generations.

The index is also important in managing the security of critical infrastructure facilities, including power plants, chemical plants and processing plants, tunnels, subways, airports, etc. For example, for stable and safe operation of subway stations, it is necessary to measure the level of harmful substances constantly. Suppose the pollution index exceeds a certain threshold. In that case, the station must be closed, as passengers' inhalation of harmful substances in high concentrations can lead to significant health problems and even death. Therefore, the index is measured at fixed intervals throughout the day, and a linear graph is generated to show the dynamics of changes in the pollution level for each parameter and all parameters in the form of an integrated pollution index.

The development and installation of monitoring systems at critical infrastructure facilities that would not only record and implement the forecast for the near future but also determine the stability of pollution is an important task in ensuring a high quality of life for citizens and environmental safety.

Conclusions to chapter 3

1. The chapter describes a method for monitoring environmental pollution parameters based on a comprehensive model for predicting time series of pollution parameters about statistical fractal analysis. The method considers the results of statistical fractal analysis to determine the direction of the time series trend, which may indicate whether the amount of pollution increases or decreases in the short term. The method also determines the average cycle length based on the V statistic, which establishes the presence of long-term memory in the time series and determines the reliability of the trend forecast calculation. In addition, the Hurst index determines whether emissions of harmful substances, particularly into the air, are stable. That is, it is shown that if the Hurst index of a time series indicates that the time series is close to random, the environmental situation in the area is unstable, and excessive emissions are

possible. This means local governments and environmental services should respond to this situation to ensure environmental safety.

2. An improved model for assessing the state of the environment in the monitoring system, which, unlike the known ones, takes into account the results of comprehensive forecasting of time series of pollution changes and can be a tool for ensuring environmental safety. The model establishes a comprehensive assessment of the state of the environment based on the method of monitoring environmental pollution parameters.
3. The direction of developing an environmental index based on the developed methods of monitoring and forecasting time series of pollution and distinguished by the consideration of prospective pollution indicators, which can be used in urban environmental monitoring and conditions of environmental uncertainty, was further developed.

CHAPTER 4. INFORMATION TECHNOLOGY FOR MONITORING ENVIRONMENTAL POLLUTION PARAMETERS TO ENSURE THE EFFICIENT OPERATION OF CRITICAL INFRASTRUCTURE FACILITIES

4.1. Information technology modules for monitoring pollution parameters

Pollution monitoring information technology modules include various systems, sensors, software, and other components that collect, analyze, and display data on the level of environmental pollution. Such modules play an essential role in detecting and controlling various types of pollution, such as air, water, soil, etc.

An important module is the module for monitoring pollution sensors. Air pollution sensors are key components of air quality monitoring systems. They measure the levels of various harmful substances in the air, which allows you to detect contaminated areas, determine the level of health hazards, and take measures to reduce them. Such sensors include:

1. Gas sensors. These sensors measure the level of various gases in the air, such as carbon dioxide (CO_2), nitrogen oxides (NO_x), sulfur oxides (SO_x), ozone (O_3), ammonia, methane, volatile organic compounds (VOCs), and others. Gas sensors can be portable for measurement at specific locations or installed on stationary monitors for continuous monitoring.

2. Particle sensors. These sensors measure particulate matter (PM_{10}, $PM_{2.5}$) and aerosols in the air, which can be finely dispersed pollutant particles. They help detect pollution that may not be visible, such as industrial debris, smoke, dust, etc.

3. Ammonia and volatile organic compound sensors. These sensors measure the level of ammonia and volatile organic compounds in the air, which can be caused by industrial processes, agricultural activities, vehicles, etc.

4. Radiation sensors. Some air pollution sensors can also measure radiation levels, such as radon, radon daughters, and other radioactive substances

that may be present in the air.

5. Meteorological sensors. Some air monitoring systems also include meteorological sensors to measure temperature, humidity, wind speed, and wind direction. This data can be used to analyze the impact of weather conditions on air pollution levels.

Water pollution sensors are also used to monitor pollution. Water pollution sensors measure the levels of various chemical and biological parameters in water environments. They help to detect contamination, identify sources of pollution, and determine the impact on the environment and human health. These include chemical sensors that measure levels of various chemicals in water, such as heavy metals (lead, mercury, cadmium), chlorine, phosphate, ammonium, arsenic, and other chemical pollutants. They also include biological contaminant sensors that detect the presence of biological contaminants in water, such as coliforms, Escherichia coli, algae, and other pathogens. Oxygen level sensors measure the level of dissolved oxygen in water, which is an essential indicator of water quality for the nutrition of aquatic organisms. pH sensors measure the pH level of water, which affects the dissolution of various substances and the ability of aquatic organisms to live. Water temperature sensors measure the temperature of water, which can indicate changes in the environment, such as global warming or thermal wastewater loads. Turbidity sensors measure the degree of turbidity in water, which can indicate the presence of particulate matter or other contaminants. Oil and oil level sensors detect the presence of oil or petroleum products in water, which helps to detect oil spills or contamination.

Soil pollution sensors measure levels of various chemicals and parameters that indicate soil contamination. They are essential in identifying contaminated areas and assessing environmental and human health impacts. These include heavy metal sensors that measure levels of heavy metals such as lead, mercury, cadmium, chromium, nickel, etc. that can be hazardous to human health and ecosystems. Oil and petroleum product sensors detect the presence of oil and petroleum products in the soil, resulting from spills, releases, or uncontrolled use of fuels. Pesticide and chemical fertilizer sensors measure the levels of chemicals used in agriculture, such as pesticides and chemical fertilizers, which can contaminate soil and negatively affect human and ecosystem health. Soil pH sensors measure the acidity or alkalinity of the soil, which can affect the availability of nutrients to plants and microorganisms in the soil. Organic matter sensors measure organic matter levels, such as polyaromatic hydrocarbons and other chemical compounds that can be toxic to living organisms in the soil.

Monitoring systems also include radiation level sensors. These systems measure environmental radiation levels, which helps identify potentially hazardous radiation sources and manage health risks.

In addition to sensors, which are a vital element of monitoring information technology, another critical component is the analytical part of the technology, which includes a forecasting method, a fractal analysis method, calculation of the contamination index, etc. The flowchart of processes in the information technology for monitoring the state of pollution is shown in Figure 4.1. The information system has a structure with the following components:

1. The technical support includes sensors that measure the level of air, water, soil pollution, etc.
2. Mathematical software includes a comprehensive forecasting model, a method of statistical fractal analysis of a time series, a method of monitoring environmental pollution parameters, a model for assessing the state of the environment, and a method for calculating the environmental index.
3. The software includes a system for monitoring pollution parameters with analytical and calculation components. The system combines technical and mathematical components.
4. Organizational support includes the principles of organizing procedures for measuring the state of the environment, storing data collected by sensors and using them for monitoring.
5. Information support provides information support for the process of collecting, cleaning data, calculating relevant environmental assessments, as well as

drawing conclusions, etc.

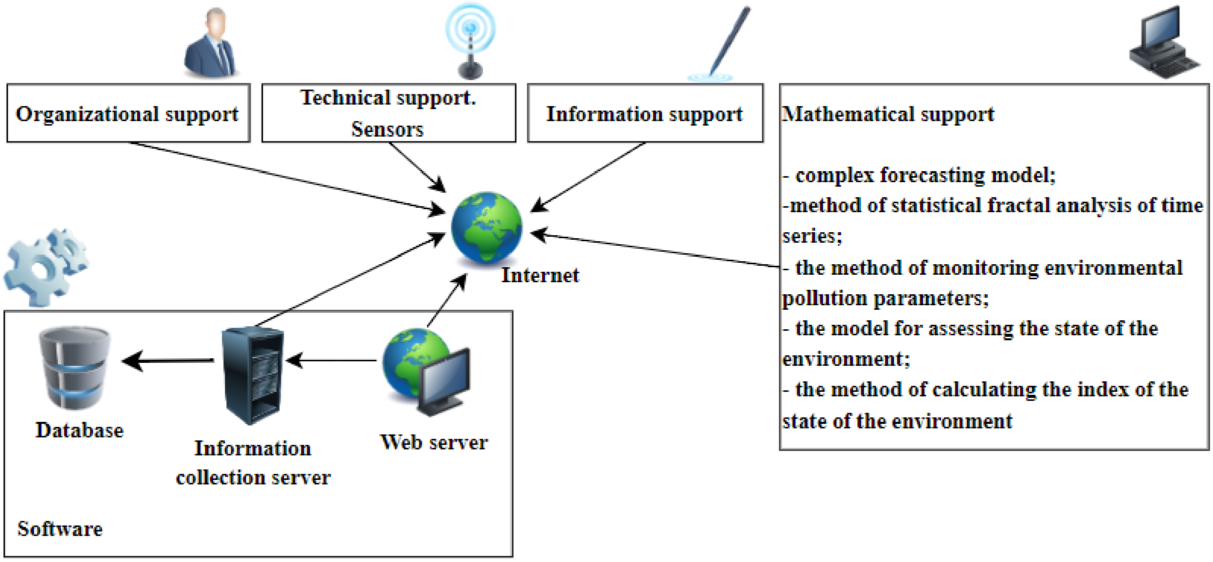


Figure 4.1. Process flowchart in the information technology of pollution monitoring

Organizational processes in environmental pollution monitoring information technology cover a wide range of actions and activities, including planning, implementing, managing, and maintaining monitoring systems. Here are some key organizational sub-processes:

1. Planning and strategic management: This process includes defining pollution monitoring objectives, selecting appropriate technologies and sensors, developing data collection and analysis strategies, and assessing risks and setting priorities.

2. Implementation of monitoring systems: This process involves selecting and purchasing the necessary equipment, installing sensors and sensors at appropriate locations, connecting to a communication and power network, configuring software, and integrating with existing systems.

3. Data collection and transmission: This process involves automated data collection from sensors and detectors, transmission over a communication network (e.g., Internet or LoRaWAN), and data storage in databases or cloud services.

4. Data analysis and processing. This process involves using analytical

methods to process and analyze the collected data, identify trends, anomalies, and other important information that allows you to make informed decisions.

5. Data presentation and visualization. This process involves displaying the collected data in an easy-to-understand format such as graphs, charts, map visualizations, etc., allowing stakeholders to analyze the information and make decisions.

6. Data management and reporting. This process includes making data available to stakeholders, creating monitoring and pollution reports and documentation, and performing regular audits and reviews to ensure data quality and regulatory compliance.

These organizational processes help to ensure that environmental pollution monitoring systems operate efficiently and provide reliable data for making informed environmental decisions.

Technical processes in environmental pollution monitoring information technology typically include installing, configuring, and managing various types of pollution sensors. The selection process selects appropriate sensors to measure specific pollution parameters according to project specifications and user needs. Sensors must be installed correctly in locations where they can effectively collect pollution data. This may include installation on stationary monitors or mobile monitoring platforms. Once installed, the sensors must be calibrated and adjusted to ensure accurate measurements. This process is usually performed using specialized hardware and software.

Pollution sensors collect data on pollution levels and transmit it to a central monitoring system. This process can be automated and carried out using wireless or wired connections. The received data is processed and analyzed to identify trends, anomalies, and other important information. This may include using various data analysis algorithms and software to visualize the results.

An essential technical process is system management and maintenance, which includes regular monitoring system management, troubleshooting, and scheduled sensors maintenance to ensure their reliable operation. The data obtained from pollution sensors is often integrated with other environmental or risk management systems to make informed decisions.

Mathematical processes in environmental pollution monitoring information technology include using various mathematical methods and models for data analysis and processing, pollution forecasting, anomaly detection, and decision-making. In the described concept, the mathematical processes include:

- a comprehensive forecasting model;
- a method of statistical fractal analysis of time series;
- a method of monitoring environmental pollution parameters;
- a model for assessing the state of the environment;
- a method for calculating the environmental condition index.

In the general concept of such technology, the mathematical processes may also include statistical analysis, which is used to identify statistically significant differences in pollution levels, establish correlations between various environmental parameters and identify pollution trends.

Modeling the spread of pollution is also used. Mathematical models, such as diffusion and dispersion models, predict the distribution of pollutants in the environment based on input data on geographic features, meteorological conditions, and other factors. Cluster analysis groups pollution zones by similar characteristics to identify the highest risk areas and determine pollution management strategies. Artificial intelligence and machine learning techniques include the use of classification, regression, clustering, and other methods to automate pollution analysis and forecasting and identify anomalies and critical dependencies in the data.

Mathematical processes also include geographic information analysis, which is used to visualize and analyze the geographic distribution of pollution, create thematic maps, and identify high-risk geographic areas. Optimization methods are also included, which are used to develop optimal pollution management strategies, such as optimal sensor placement, optimal monitoring network planning, etc.

Software processes in environmental pollution monitoring information technology include developing, implementing and maintaining software for collecting, analyzing and visualizing pollution data. The first necessary process is software development. This process involves analyzing software requirements, designing the system architecture, developing code, testing, and documenting software for pollution monitoring systems. The second process is integration with sensors and equipment. The software must be integrated with various pollution sensors, communication networks, and other equipment to ensure data collection and processing. To store and manage large volumes of pollution data, efficient databases must be developed that consider the specifics of the data and the needs of users. The monitoring software should include modules for processing and analyzing the collected data, including statistical analysis, modeling of pollution spread, machine learning, and other methods.

An important aspect is the ability to visualize pollution data in an easy-to-understand format, such as graphs, charts, maps, etc., which allows users to analyze the information effectively. It is also necessary to develop convenient and intuitive user interfaces for interacting with pollution monitoring software, including web interfaces, mobile applications, and others.

The last process is data management and reporting. The software should provide the ability to manage and store pollution data and generate reports and analytical documents for users. Since pollution data can be sensitive, it is important to protect it from unauthorized access and system hacking.

Information processes in environmental pollution monitoring information technology cover all aspects of data collection, processing, analysis, and use to assess the state of the environment. Based on the processed data, reports on the state of the environment can be automatically generated, and notifications can be sent if anomalies occur or if the permissible pollution levels are exceeded.

4.2. Results of using information technology for monitoring environmental pollution parameters to ensure environmental safety

The application of the developed information technology primarily concerns environmental safety in the People's Republic of China. After the implementation of the monitoring system in China, it can be distributed to other countries worldwide. The monitoring technology was introduced at Yancheng Polytechnic College. The university has several projects to develop systems and models for assessing and monitoring air quality or environmental pollution. The Beijing metropolitan area is significant for creating measures to reduce air pollution.

A time series of pollution parameters in Beijing was selected to test the performance of the developed models, methods, and monitoring system [110]. This dataset includes six major air pollutants and six relevant meteorological variables at several locations in Beijing.

This dataset includes hourly air pollutant data from 12 nationally monitored air quality monitoring sites. The air quality data is obtained from the Beijing Municipal Environmental Monitoring Center. The meteorological data at each air quality monitoring site is coordinated with the nearest weather station of the China Meteorological Administration. The period from March 1, 2013, to February 28, 2017. The pollution indicator recorded in this time series is PM2.5. PM2.5 indicators are often included in air quality reports provided by environmental authorities and companies. PM2.5 refers to atmospheric particles (PM) less than 2.5 micrometers in diameter. These particles can be hazardous because their size allows them to penetrate the lungs and even the bloodstream, leading to serious health problems. Measuring the level of PM2.5 in the air is an essential indicator of air quality because it can be particularly harmful to health.

If PM2.5 levels exceed the recommended limits, it can lead to various health problems, such as respiratory problems, cardiovascular disease, asthma exacerbation, and other diseases. Therefore, controlling and monitoring the level of PM2.5 in the air is an important task to ensure the safety and health of the public. To measure PM2.5 levels in the air, special sensors are used that can be installed in atmospheric monitors or special devices. These sensors can detect and measure PM2.5 levels in real-time, which allows for a prompt response to any high levels of pollution and measures to reduce it.

Time period: from March 1, 2013 to February 28, 2017. 12 files in total. Each contains 35064 rows and 18 columns. There are empty values in the columns. Columns with numerical values were filled in using the principle of interpolation of missing values, taking into account the nearest values in the row. As it turned out, there are no duplicates. The time series of the PM2.5 parameter of air pollution was visualized (Fig. 4.2).

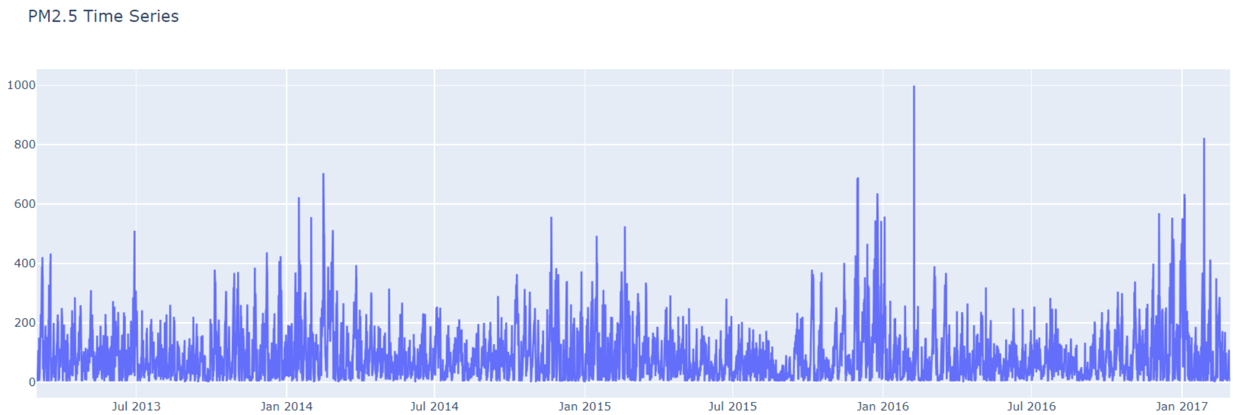


Figure 4.2. Time series of PM2.5 air pollution parameter

The figure shows the emissions; the data is hourly. It was decided to smooth the series. Figure 4.3 shows the smoothed time series of PM2.5 air pollution. The smoothing was performed using the moving average method by day. Also, Figure 4.4 shows the time series smoothed by weeks, and Figure 4.5 shows the smoothed time series by months (30 days). It can be seen that PM2.5 particles in the air decrease by summer. In winter, the number of particles increases sharply. Figure 4.5 shows that a sharp increase in harmful particulate matter 2.5 increases in January-February. The number decreases by the end of summer and early fall. This may be influenced by vegetation (trees actively produce oxygen in warm weather), furnace furnaces (in cold weather) and other factors. In Fig. 4.6, the input time series was smoothed by year. The highlighted trend shows a downward trend in the total amount of PM2.5 particle emissions in the air, reaching its minimum in late 2015 and early 2016.

Figures 4.7(a) through 4.7(l) show the air pollution indicators for different regions in the Beijing area in 2013-2017. The name of the station where the measurement was made is indicated in the first column. The red curve is PM2.5, and the blue curve is PM10. Figures 4.8(a) - 4.8(l) show the time series of air pollution indicators for different regions in the Beijing area in 2013-2017. The name of the station where the measurement was made is indicated in the first column. The red curve is NO2, the blue curve is SO2, the green curve is CO, and the purple curve is O3.

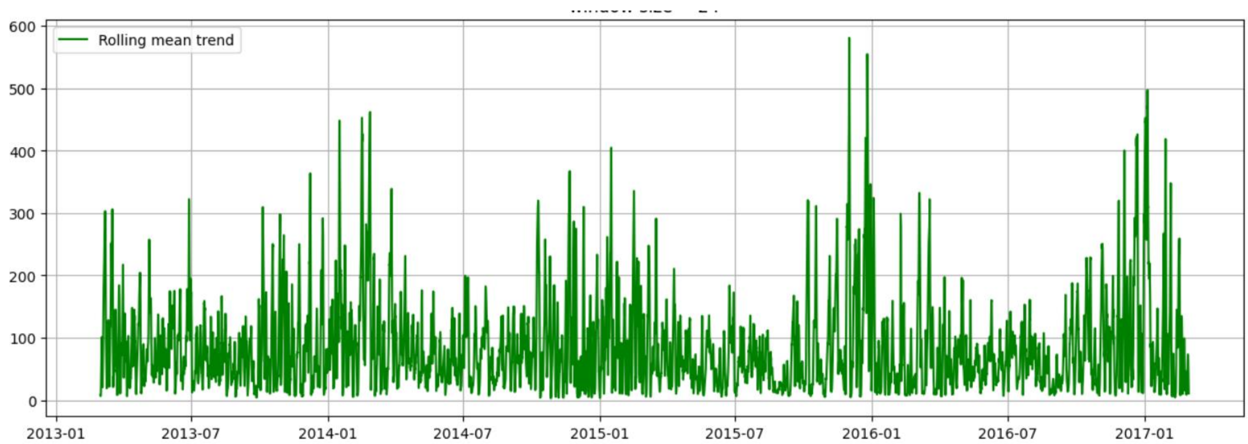


Figure 4.3. Smoothed time series of PM2.5 air pollution by day using the moving average method.

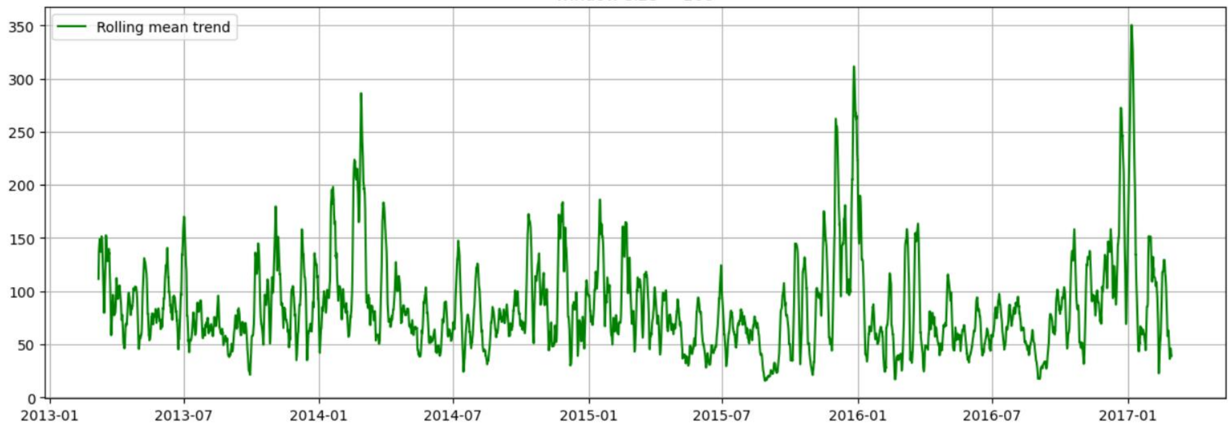


Figure 4.4. Smoothed time series of PM2.5 air pollution by week by the moving average method

Figure 4.5. Moving average smoothed time series of PM2.5 air pollution by month

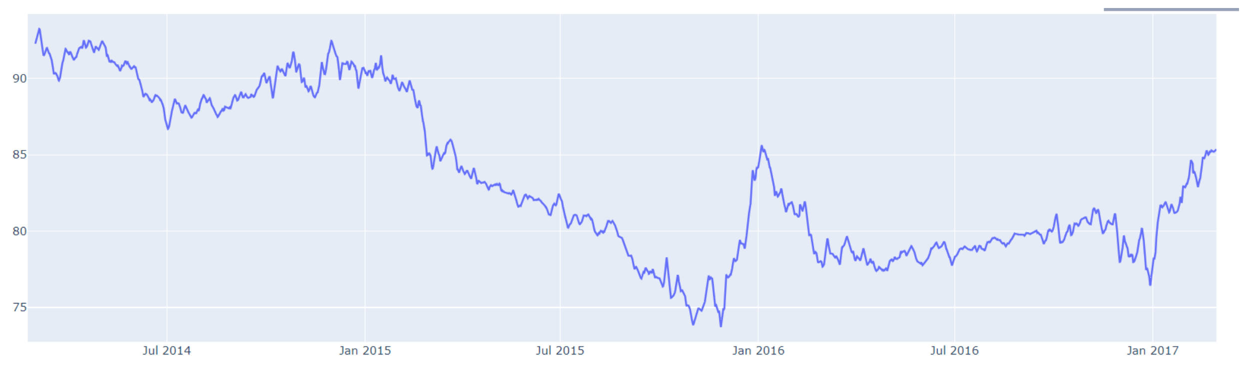
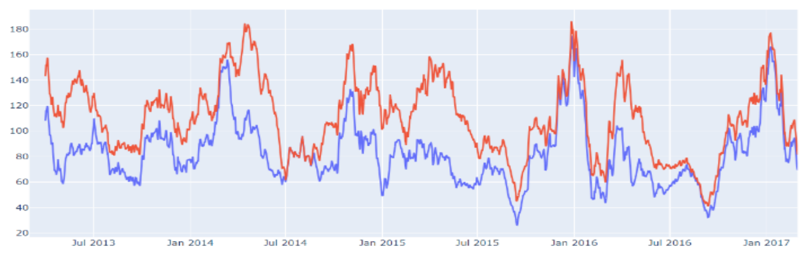
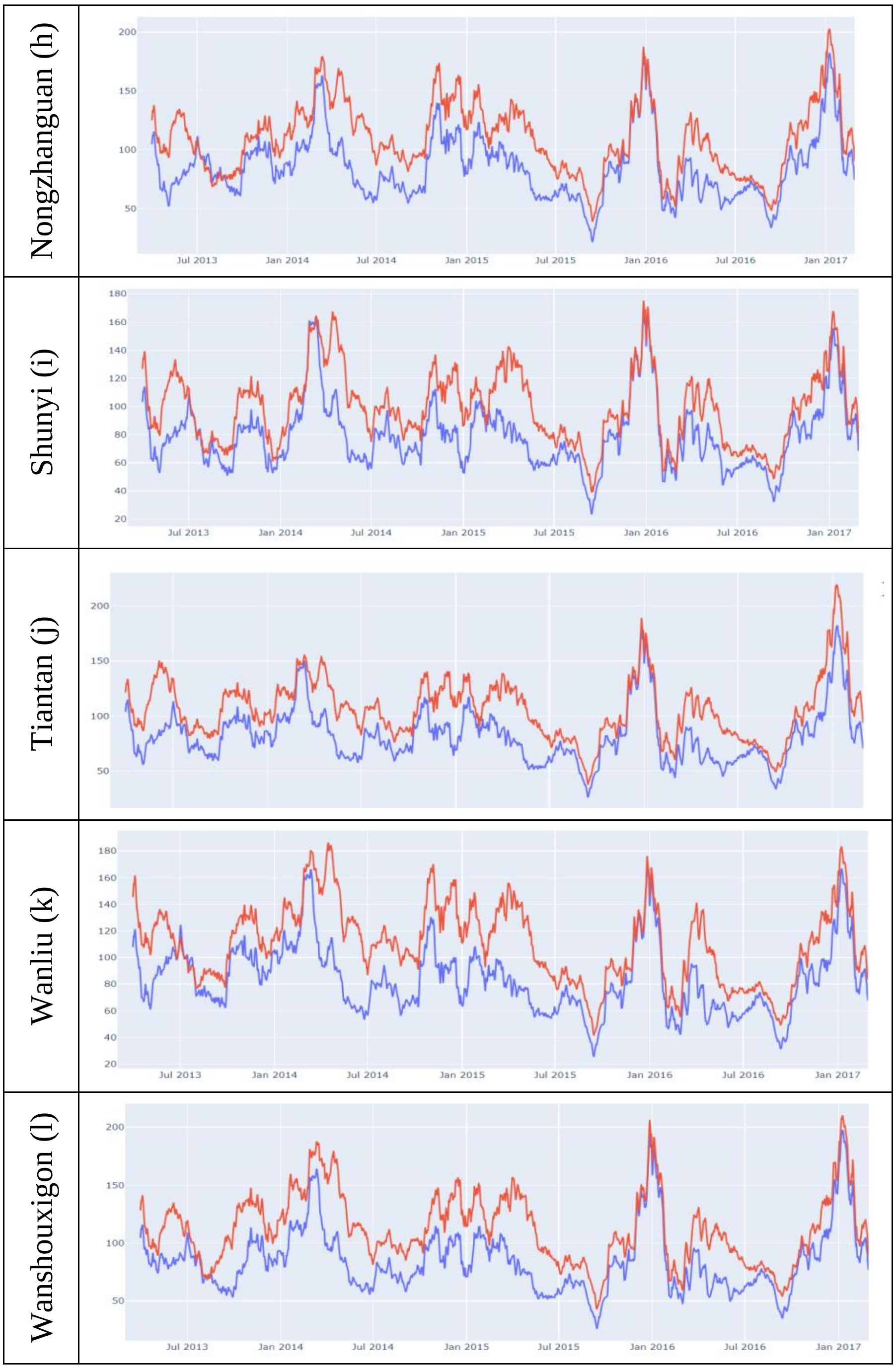


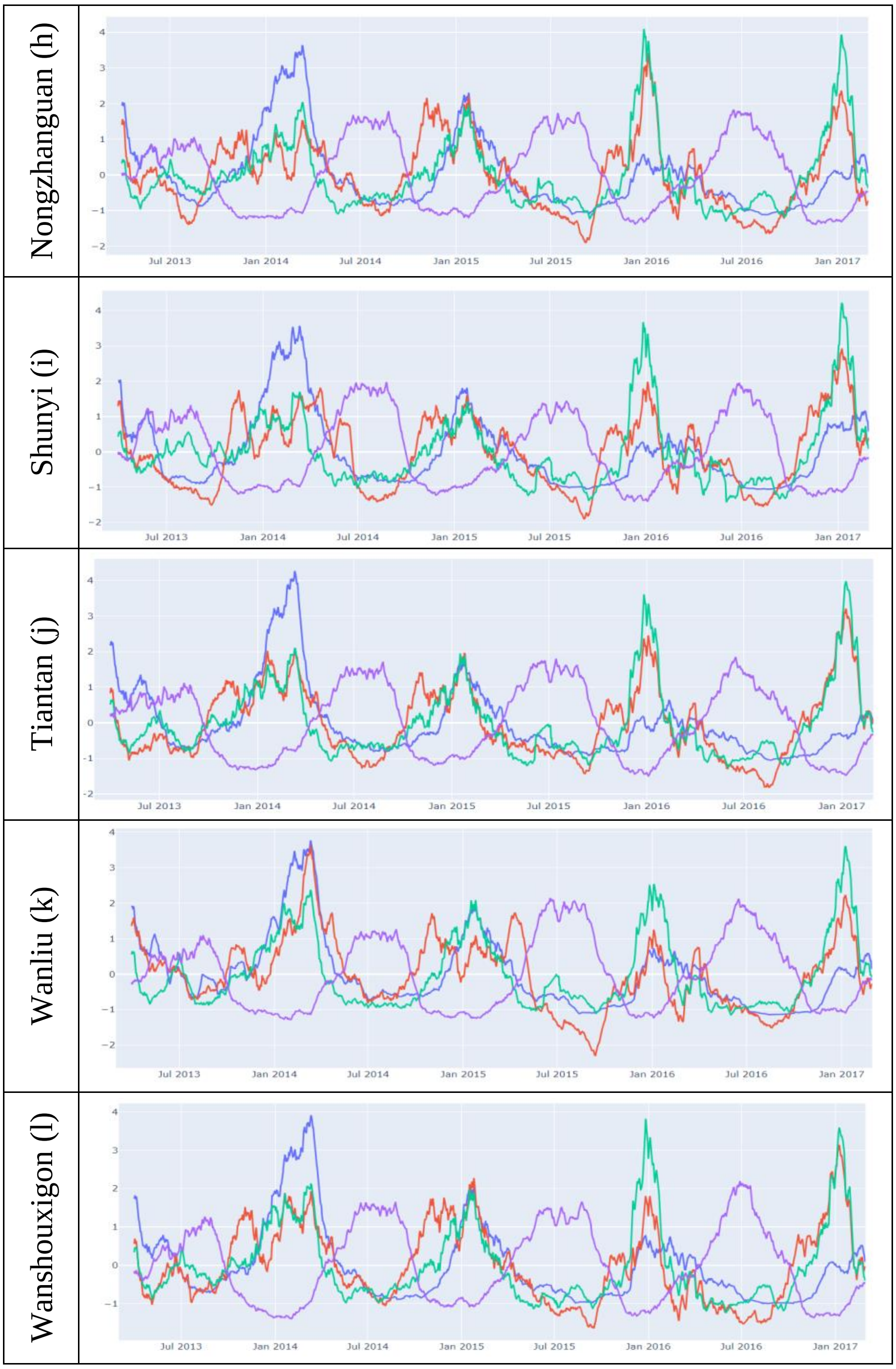
Figure 4.6. Moving average smoothed time series of PM2.5 air pollution by year

Aotizhongxin (a)	
Changping (b)	
Dingling (c)	
Dongsi (d)	
Guanyuan (e)	
Gucheng (f)	
Huairou (g)	



Figures 4.7 (a) - (l). Air pollution indicators for different regions in the Beijing area in 2013-2017. The name of the station where the measurement was made is indicated in the first column. Red curve - PM2.5, blue curve - PM10

Aotizhongxin (a)	
Changping (b)	
Dingling (c)	
Dongsi (d)	
Guanyuan (e)	
Gucheng (f)	
Huairou (g)	



Figures 4.8 (a) - (l). Air pollution indicators for different regions in the Beijing area in 2013-2017. The name of the station where the measurement was made is indicated in the first column. The red curve is NO_2, the blue curve is SO_2, the green curve is CO, and the purple curve is O_3.

Studying the dynamics of pollution change is essential for forecasting and assessing the environmental friendliness of a given region. At the next stage, according to the described method, a statistical fractal analysis of time series of environmental pollution parameters in Beijing for various pollutants was performed. The indicators PM2.5 and PM10 were selected. The obtained results indicate that all-time series of environmental pollution parameters are persistent; some of the series is close to random.

For example, at Huairou station, the PM10 indicator of the Hurst exponent $H\left(Q^h\right)=0.588$ at the theoretical limit of randomness $H_h^T=0.545$. The presence of instability in emissions of large PM10 particles into the air may be because one of China's largest concrete mix producers, MUHU (China) Construction Materials Co., Ltd. is located in this region, as well as other industries.

Also, the Hurst index for the Guanyuan region (PM10 pollution indicator) is $H\left(Q^h\right)=0.567$. The volatility of emissions may be because Guanyuan's economy is based on a diverse heavy industry and mining. Plant 821, a former large plutonium production reactor now used for nuclear waste reprocessing, is near Guanyuan.

The Shunyi region also has a low Hurst value. In general, the region has a large number of industries that can pollute the air, but such a low Hurst value for PM10 $H\left(Q^h\right)=0.572$ may indicate the presence of unreasonable emissions since few industries in the region would emit large amounts of PM10. All series are generally persistent, which means that emissions in these regions are controlled, i.e., the industries do not emit harmful substances above the planned levels. Figures 4.8 and 4.9 show a visualization of the calculation of Hurst's indices for the time series of PM2.5 and PM10 pollution parameters for the regions: Aotizhongxin, Changping, Dingling, Dongsi, Guanyuan, Gucheng, Huairou, Nongzhanguan, Shunyi, Tiantan, Wanliu, Wanshouxigon.

The Aotizhongxin station is in Beijing and this region is characterized by significant automobile traffic, which generally shows an excess of PM2.5

concentration. The Hurst values for PM2.5 and PM10 are not large, but the series are persistent.

Changping station is characterized by indicators similar to those of the Aotizhongxin station. The area has emissions from cars in general. Xiaomi's Smart Factory is also located in the area, but it does not emit many harmful substances.

Even more stable indicators were found for the Dingling region. There are no plants with significant emissions of harmful substances in the region. Similar results were recorded for the Dongsi, Gucheng, Nongzhanguan, Tiantan, Wanliu, and Wanshouxigon regions.

The average value of the cycle c for all time series is 5-7 points, which may indicate a clear cycle of about one week. This is likely explained by the increased car traffic on busy days and reduced traffic during weekends. Alternatively, factory emissions have less of an impact on the average cycle size of the air pollution time series. Of course, this study should have also considered the water and soil pollution level in the areas adjacent to the hazardous production facilities. However, more than this data was needed for analysis.

Overall, the system showed satisfactory results for environmental monitoring. The estimates obtained for the regions where hazardous industries are located are significant. This means the system can be explicitly used to monitor pollution near critical infrastructure facilities to ensure environmental safety.

Due to significant air, water, and soil pollution, Beijing's environmental conditions have traditionally been problematic. Air pollution was particularly a severe problem in Beijing due to the large number of cars, industrial plants, and construction. This led to significant deterioration in air quality and health problems for residents.

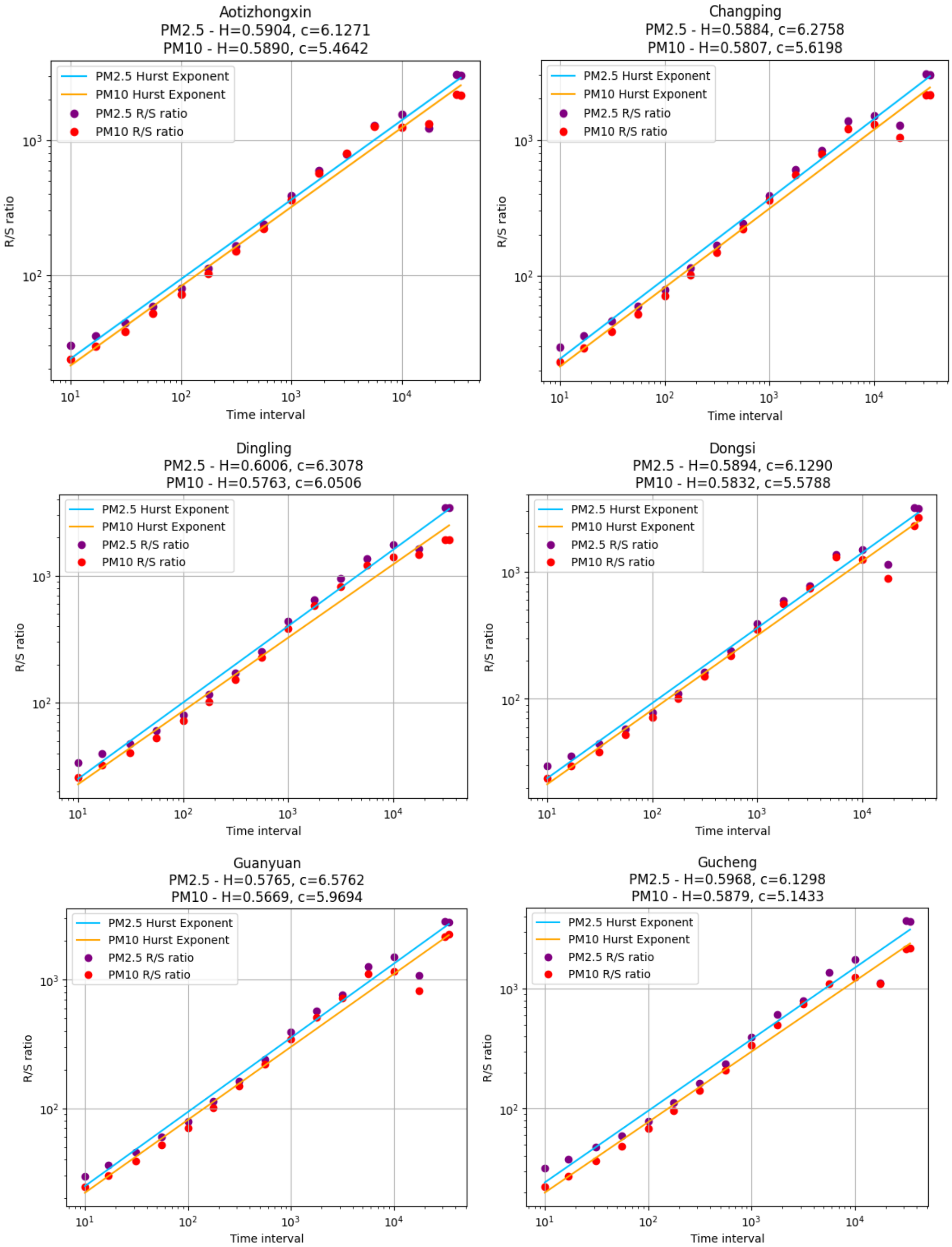


Figure 4.8. Visualization of hurst exponent calculation for time series of PM2.5 and PM10 pollution parameters for regions: Aotizhongxin, Changping, Dingling, Dongsi, Guanyuan, Gucheng.

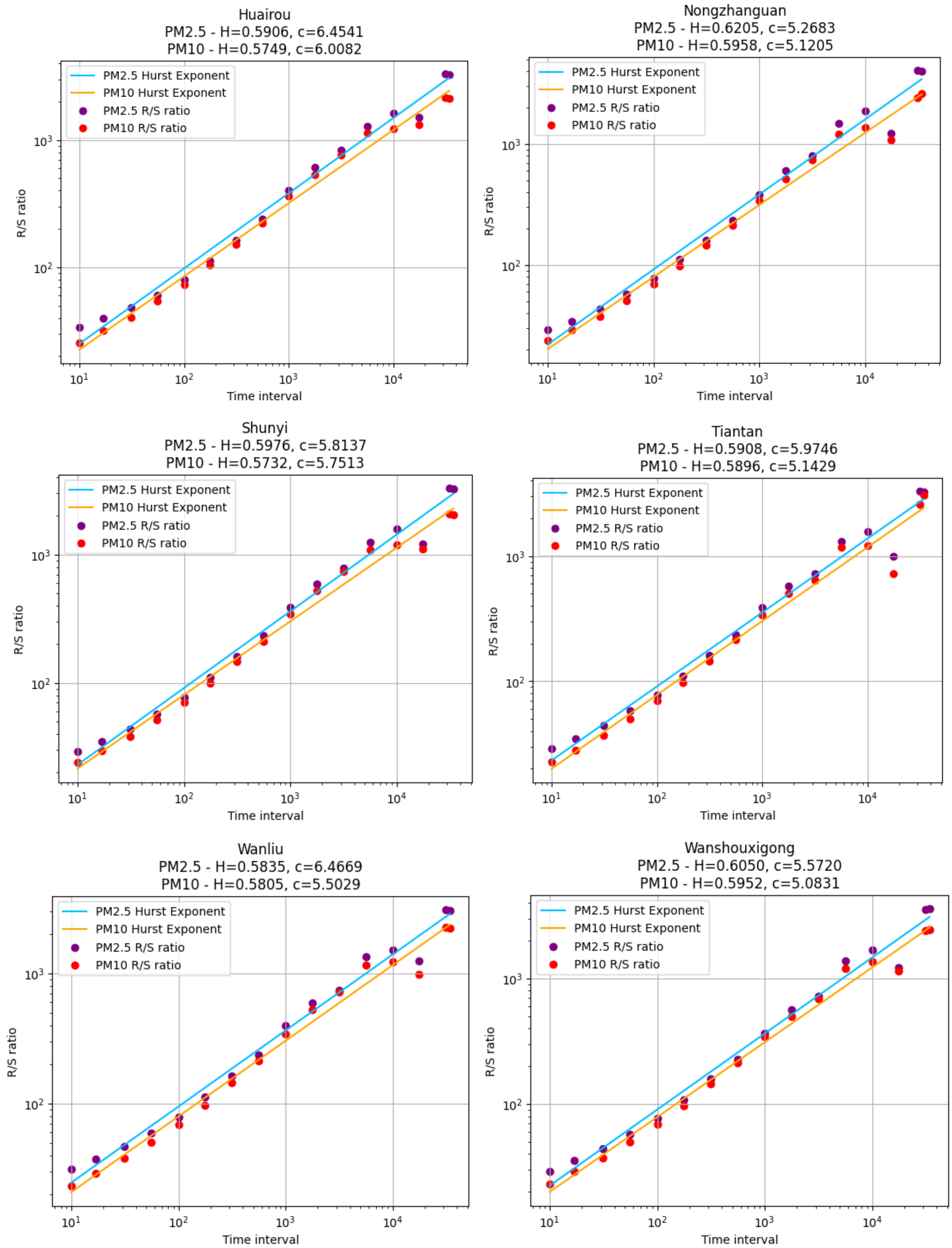


Figure 4.9. Visualization of hurst exponent calculation for time series of PM2.5 and PM10 pollution parameters for regions: Huairou, Nongzhanguan, Shunyi, Tiantan, Wanliu, Wanshouxigon.

However, the Beijing government has taken several measures to reduce pollution and improve the environment. For example, introducing strict emission standards for enterprises, promoting energy-efficient technologies, developing public transportation, and investing in renewable energy. These measures have helped reduce pollution levels and improve air quality in Beijing. However, although some progress has been made, environmental problems in Beijing still need to be solved. At the same time, some pollution may go beyond the city limits and be linked to other regions of China. Thus, monitoring the state of the environment and taking measures to improve it continues to be essential tasks for the Beijing authorities.

After performing statistical fractal analysis, it is possible to make a forecast using the developed complex model. The ARIMA model was also chosen for forecasting. The RMSE, MAE, MAPE, and MSE errors were calculated based on the forecasting results.

RMSE (Root Mean Square Error) is a metric for measuring the accuracy of a forecasting model. It measures the difference between the values predicted by the model and the actual values in the data sample. RMSE is measured in the same units as the input data and indicates the root mean square deviation of the predicted values from the actual values:

$$\mathrm{RMSE}=\sqrt{\frac{1}{r}\sum_{i=1}^{r}\left(q\left(t_{n+i}\right)-q\left(t_{n+i}\right)\right)^{2}}, \tag{4.1}$$

where $q\left(t_{n+i}\right)$ - actual values, $q\left(t_{n+i}\right)$ - forecast values, r - forecast period.

MAE (Mean Absolute Error) is another metric for measuring the accuracy of a forecasting model. It calculates the average absolute deviation value between the actual and predicted values. MAE is measured in the same units as the input data and indicates the average absolute deviation of the predicted values from the actual values. As with other metrics, the lower the MAE value, the better the model predicts the data. MAE looks at the magnitude of the deviations without regard to their direction, so it is less sensitive to large deviations, which can be helpful in some situations:

$$MAE = \frac{1}{r}\sum_{i=1}^{r}\left|q(t_{n+i}) - q(t_{n+i})\right|, \tag{4.2}$$

where $q(t_{n+i})$ - actual values, $q(t_{n+i})$ - forecast values, r - forecast period.

MAPE (Mean Absolute Percentage Error) is a metric for measuring a forecasting model's accuracy, which measures the percentage deviation between actual and predicted values. MAPE is expressed as a percentage and provides an overall assessment of the deviations of the forecasting model from the actual data:

$$MAPE = \frac{100}{r}\sum_{i=1}^{r}\frac{q(t_{n+i}) - q(t_{n+i})}{q(t_{n+i})}, \tag{4.3}$$

where $q(t_{n+i})$ - actual values, $q(t_{n+i})$ - forecast values, r - forecast period.

MSE (Mean Squared Error) is a metric for measuring a forecasting model's accuracy, which measures the average square deviation between actual and predicted values. Mathematically, MSE is calculated as the average of the squared deviations:

$$MSE = \frac{1}{r}\sum_{i=1}^{r}\left(q(t_{n+i}) - q(t_{n+i})\right)^2, \tag{4.4}$$

where $q(t_{n+i})$ - actual values, $q(t_{n+i})$ - forecast values, r - forecast period.

Figures 4.10, 4.11 show the results of forecasting the time series of PM2.5 and PM10 pollution parameters for the indicators from Aotizhongxin station using the ARIMA model.

As we can see, the dynamics of pollution parameters for PM2.5 and PM10 are approximately repeated. At the end of the observations, emissions for these pollution parameters increase. This indicates the emergence of industries or sources that emit additional pollution in the Aotizhongxin region.

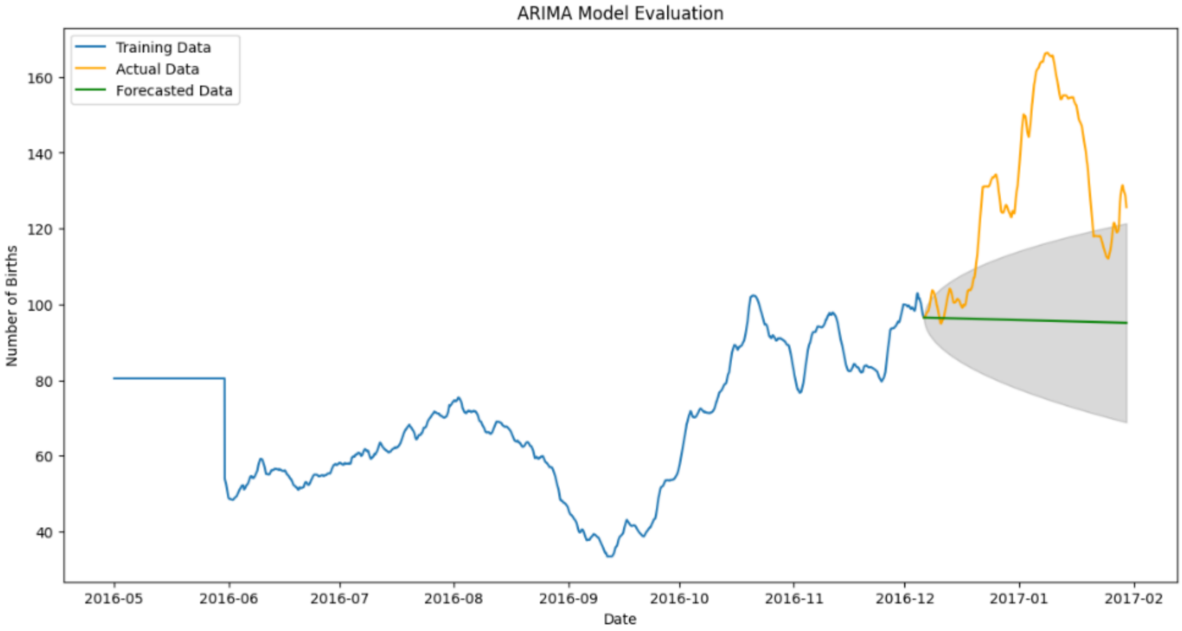


Figure 4.10. Results of forecasting the time series of PM2.5 pollution indicators in the Aotizhongxin region using the ARIMA model, RMSE = 39.44, MAE = 32.73, MAPE = 23.24, MSE = 1555.73.

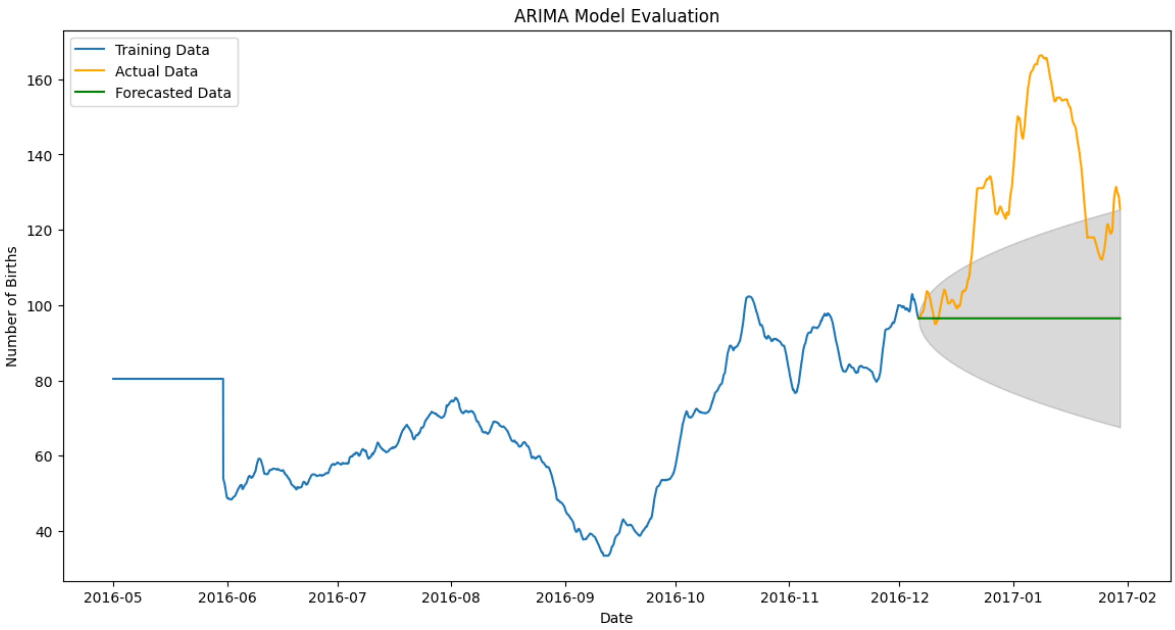
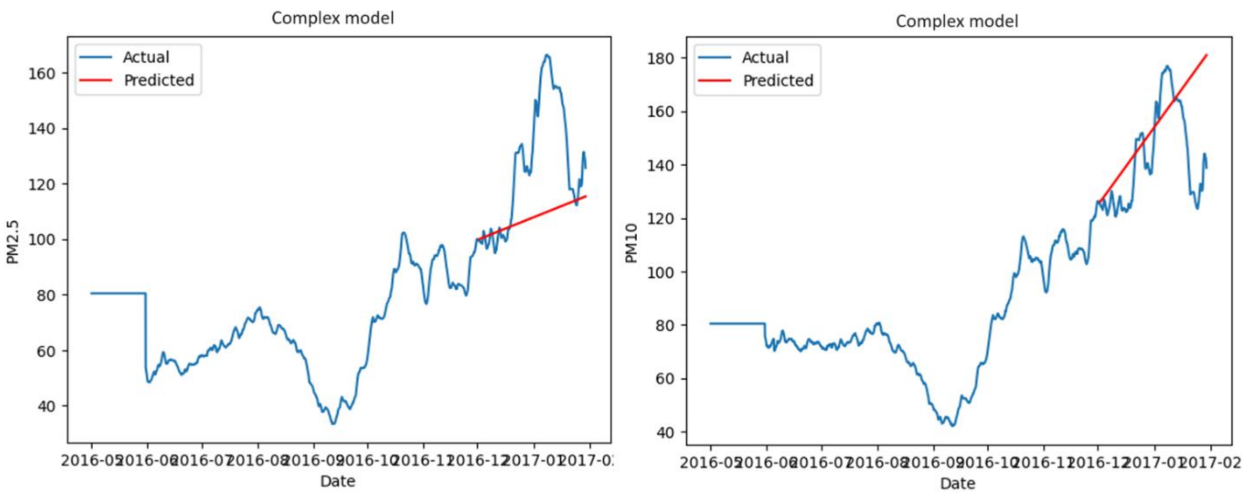


Figure 4.11. Results of forecasting the time series of PM10 pollution indicators in the Aotizhongxin region using the ARIMA model, RMSE = 38.74, MAE = 32.04, MAPE = 22.72, MSE = 1501.09.

Figures 4.11 (a) - 4.11 (b) show the results of forecasting the time series of PM2.5 and PM10 pollution indicators in the Aotizhongxin region using the integrated model, considering the results of statistical fractal analysis. The forecasting results for the PM2.5 parameter are RMSE=27.448, MAE=20.155, MAPE=13.971, MSE=753.412. The forecasting results for the PM2.5 parameter are RMSE=21.021, MAE=15.193, MAPE=11.274, MSE=441.880. The accuracy of the integrated model is higher than that of the ARIMA model. The MAPE for the ARIMA model is at least 22.72%, while for the complex model it is 11.27%. That is, the accuracy of the complex model is 2 times higher. The forecasting accuracy still needs to improve. This is because the time series are close to random and weakly persistent. Therefore, for effective monitoring, it is enough to indicate the trend in the values of pollution parameters. As we can see, the trend is upward in this case, meaning that pollution will increase. The change in the Hurst index in the dynamics indicates that weak persistence will be maintained in the future.



(a) (b)

Figure 4.12 (a) – (b). Results of forecasting time series of PM2.5 and PM10 pollution indicators in the Aotizhongxin region using a complex model with the results of statistical fractal analysis.

The significant increase in pollution levels during 2013-2017 indicates a deterioration in the environmental situation. Other pollution indicators are analyzed similarly. It should be noted that different types of pollution correspond to different pollutants. If the pollution parameter is exceeded, the regional authorities can control emissions through communication with the relevant industries.

So, in general, forecasting time series of environmental pollution parameters and developing information technologies for monitoring pollution levels are of outstanding global importance for environmental safety for several reasons:

1. Preventing environmental crises. Predicting pollution time series allows you to detect pollution trends and patterns in time, which can help avoid potential environmental crises such as air, water, or soil pollution over a large area.
2. Ensuring public health. Monitoring information technologies provide data on the level of pollution, which can become the basis for taking measures to protect public health. Forecasting allows us to predict and respond to the situation's future development adequately.
3. Efficient use of resources. Pollution monitoring helps identify pollution sources and effectively allocate resources to reduce and control them.
4. Global monitoring of pollution and using standard technologies for data analysis are essential for cooperation between countries in ecology and for developing joint strategies to reduce pollution.
5. Protection of ecosystems. Pollution monitoring helps to detect changes in ecosystems and natural resources in time, which allows for measures to be taken to protect and restore them.

4.3. Use of information technology for monitoring pollution parameters to improve the efficiency of management of some critical infrastructure facilities

Critical infrastructure is defined as key facilities, systems, networks, and services essential to the functioning of society and the economy and highly vulnerable to disruption, destruction, or unavailability. These facilities are critical because their disruption or unavailability could seriously affect national security, public safety, the economy, and the general welfare. Critical infrastructure may include such sectors as energy, transportation, water, communications, finance, healthcare, food, information technology, and many others. Examples of critical infrastructure include:

- power plants, substations and electrical networks that provide electricity for cities, towns and industrial enterprises;
- railroad networks, roads, airports, ports, bridges and tunnels that provide transportation and logistics;
- water intake stations, water transport, water supply and sewerage systems that provide access to drinking water and sanitation;
- telephone networks, Internet providers, satellite communication systems that provide communication and data transmission;
- Banks, financial institutions and payment systems that ensure the functioning of the financial system and financial transactions;
- hospitals, clinics, laboratories and other healthcare facilities that provide medical care and treatment.

Almost all critical infrastructure facilities must operate in an environmentally safe manner. However, there are several critical facilities for which environmental safety is paramount. That is, in the event of a breach of safety conditions, such a facility may cease to function, threatening the sustainability of the region's development and endangering the lives and health of its residents.

Such critical infrastructure facilities include power plants. Air quality measurement is essential at power plants, especially coal or other renewable energy sources. Emissions of harmful substances into the atmosphere can have severe consequences for the health of employees and residents of the surrounding areas. Some of the critical pollution parameters that must be measured to control emissions from coal-fired power plants include:

- sulfur oxides (SOx) and nitrogen oxides (NOx). These substances are formed during the combustion of coal and can cause acid rain, as well as respiratory and other health problems;

- particulate matter (PM10, PM2.5). Coal dust microparticles can penetrate the respiratory tract and cause respiratory diseases and other health problems;

- carbon oxides (CO and CO2). Significant CO2 emissions from coal-fired power plants can lead to climate change and global warming;

- heavy metals (mercury, cadmium, lead), etc.

Each country's relevant organizations and legal regulations determine the pollution level standards. For example, the European Union has the Industrial Emissions Directive, which sets maximum permissible emission levels for various pollutants. In the United States, regulations are governed by the Environmental Protection Agency (EPA), which sets national standards for air quality and emissions. Using the developed information technology, it will be possible to predict what level of pollution will be observed in the future and what is its cyclical nature. The Hurst parameter will also help to determine how sustainable the emissions from power plants are.

Other critical infrastructure facilities are processing plants and chemical plants. They pose a massive threat to the environment in the region, but their operation is essential for economic development. In addition, the operation of such systems should be optimized as much as possible, as violations of time limits or disruptions in the organization of such plants can lead to unpredictable consequences. Some chemicals can be toxic, carcinogenic, mutagenic, or affect the nervous system. The main pollution parameters that should be measured to control emissions from chemical plants include:

- emissions of toxic substances. This parameter can include substances that have a toxic effect on human health or the environment, such as heavy metals, chlorine, fluorine, hydrogen chloride, hydrogen chloride, phosphorus chloride, nitrogen oxides, sulfur oxides, ammonia, benzene, toluene, formaldehyde, dioxins, etc;

- emissions of harmful gases. This parameter may include carbon monoxides (CO, CO_2), nitrogen oxides (NO_x), hydrogen sulfide (H_2S), ammonia (NH_3) and other gases that may hurt health and the environment;

- Smoke and particulate emissions. Emissions of particulate matter, such as soot (PM10, PM2.5), can be hazardous to the respiratory tract and cause respiratory diseases;

- emissions of organic substances. This parameter can include a variety of organic compounds, such as volatile organic compounds (VOCs), which can have toxic effects on health and the environment.

The relevant organizations and legal regulations in each country also determine standards for contamination levels. Legislation, environmental regulations, and international agreements often regulate limits and standards for pollution levels. The creation of information technology for monitoring environmental pollution parameters is significant for the operation of such facilities. This issue is particularly relevant for the People's Republic of China. The development of the chemical industry in the People's Republic of China is one of the fastest in the world. China has become one of the largest producers of chemical products and is an essential player in the global chemicals market.

Recycling plants face similar environmental safety issues. Plants that process waste or garbage can release unpleasant or dangerous odors and substances into the atmosphere. Measuring air pollution levels can help identify these emissions and take steps to reduce them.

A special mention should be made of the facilities that make a city sustainable, such as transportation infrastructure, especially tunnels and subways. Tunnels and subways can accumulate high levels of emissions from vehicles and trains. Measuring air pollution levels can be essential to ensure the safety and comfort of passengers and staff. Emissions in tunnels and subways can threaten human health if they contain harmful substances or particles that people in such enclosed spaces can inhale. In tunnels, harmful substances such as carbon monoxide are recorded, which can arise from fuel combustion in vehicles and potentially affect health at high concentrations. Also, NOx emissions can be recorded in tunnels and subways, resulting from fuel combustion and can cause respiratory diseases. In addition, particulate matter PM10, PM2.5, and organic substances such as benzene, toluene, and others are often detected in the subway. Different organizations and governments can set the standards for pollution levels in tunnels and subways, taking into account the specifics of a particular region and the technical capabilities to reduce emissions and improve air quality. Such standards may be legally regulated and enforced.

Also crucial for ensuring environmental safety, which critically affects the quality of human life, is measuring water pollution in water supply systems and water networks, air in public places, and soil on agricultural land.

Currently, the information technology for monitoring environmental pollution parameters has been tested on a dataset of pollution levels in Beijing (People's Republic of China) at 12 monitoring stations. The study concerned air emissions of PM10 and PM2.5 particles. The results are part of a research project in this area that was implemented at Yancheng Polytechnic College. As shown in [89], although an improvement in the environmental situation in China was recorded during 2012-2016, these estimates could be more optimistic. Many steps still need to be taken to ensure environmental sustainability. The information technology for monitoring environmental pollution parameters developed in this thesis opens up opportunities to study not only the amount of emissions and forecast the amount of emissions for different types of pollutants but also the sustainability of emissions. The technology allows us to determine whether emissions have been constant over a certain period or whether spontaneous, unregulated emissions characterized them.

Environmental pollution levels, pollution forecasts, and the sustainability of environmental emissions can provide significant helpful information for local governments, environmental control services, and the state regarding environmental safety management and critical infrastructure management. Information on pollution levels and forecasts can help assess potential environmental and critical infrastructure risks. This allows timely measures to be taken to prevent possible negative consequences. Knowledge about the forecast of pollution levels and the sustainability of emissions of harmful substances allows for developing emergency plans and timely responses to crises. Information on the pollution level can be used to assess the impact on human health and ecosystems, which allows for the development of effective strategies to reduce this impact. Knowledge about the pollution level can serve as a basis for developing and implementing environmental standards and regulations aimed at reducing emissions of harmful substances and improving environmental quality. Information on the pollution level can also be used to assess the effectiveness of measures to reduce environmental pollution. This allows us to adjust management strategies to achieve better results.

In the future, we plan to develop this topic and implement the results obtained in the environmental services activities in the People's Republic of China. This will improve the quality and safety of citizens' lives. It will ensure continuous monitoring and forecasting of the level of environmental pollution. This will improve the efficiency of environmental safety management in the region and ensure the stable operation of critical infrastructure facilities.

Conclusions to chapter 4

1. The information technology for monitoring environmental pollution parameters was described, which is distinguished by taking into account the results of analysis and forecasting of changes in pollution parameters and offers an assessment of the state of the environment, which provides opportunities for quantitative assessment of the environmental situation in the region. Information technology includes methods for collecting

information, a method for monitoring environmental pollution parameters, a model for assessing the state of the environment in the monitoring system, a method for calculating the environmental condition index, time series forecasting models, a method for statistical fractal analysis of time series, etc. All of these components allow for a qualitative analysis of the region's environmental condition and predict its future change. This is important for managing the safety of critical infrastructure facilities, such as chemical plants and energy facilities.

2. The information technology for monitoring pollution parameters based on a monitoring method that uses a comprehensive forecasting model, time series trend prediction, and statistical fractal analysis was verified. The verification was carried out using the example of a time series of environmental pollution parameters in different districts of Beijing, which were recorded from 2013 to 2017. The calculated errors in forecasting and assessing the state of the environment show the effectiveness of the development of such information technology and the relevance of this development for use by the city's environmental services and government agencies. Acts on implementing the results of work within the framework of research projects of Yancheng Polytechnic College (Appendix A).

CONCLUSIONS

The dissertation is devoted to developing methods, models, and information technology for monitoring environmental pollution parameters and environmental safety management. The practical significance of the results obtained is that the developed methods, models, and information technology are essential steps in developing the theoretical and practical framework for ensuring the sustainability and environmental friendliness of the development of cities and other regions of the country. The resulting tool is important in practice for environmental services, local authorities and government agencies that provide environmental control, as well as for maintaining a stable state of the environment of the surrounding core. In the long term, using the developed methods and models will positively impact the development of environmental monitoring in urban planning. Also, the described information technology for monitoring the level of environmental pollution is essential for managing the safety of critical infrastructure facilities, such as energy facilities, processing plants and, chemical plants, etc. In addition, monitoring pollution levels is essential for the health and life of people in tunnels, subways and, airports, etc. The main provisions and results of the research have been implemented and applied in the activities of Yancheng Polytechnic College.The following results were obtained:

1. The basic concepts and features of environmental monitoring are described. The necessity of increasing monitoring efficiency and the main approaches to their solution by improving methods and technologies are substantiated. The analysis of the properties of time series of pollutants shows that they can be classified into three classes: substances with a pronounced seasonal component, substances with a pronounced trend, and random variables. Such a classification allows for a better selection of forecasting and data transformation methods that can be used more effectively for each class of substances. The problem of environmental monitoring has been formalized in two formulations: point and plane. The main stages of environmental monitoring are highlighted. These are

collecting data on the state's history, monitoring the current state and predicting the state of environmental pollution in the future. Approaches and requirements for technical means at each stage are proposed. A review of known systems for monitoring air, water and soil pollution. The importance of the technical component is shown. Fundamental differences and new trends in using innovative technologies for monitoring environmental pollution parameters are identified. A scientific hypothesis defines the author's vision of an environmental monitoring organization by combining software and hardware systems and using trend models to predict environmental pollution parameters. It is noted that constructing an air pollution monitoring system is also necessary to safely operate some critical infrastructure facilities, including power plants, processing and chemical plants, airports, tunnels and subways, etc.

2. The second section describes a comprehensive model for forecasting time series of environmental pollution indicators, considering the aggregation of various forecasting models formed based on a predictive statistical analysis of pollution indicators and having an adaptive nature. The model differs from the known models by providing the ability to adapt the model parameters to changes in the state of the environment, which is especially important when using such models in environmental monitoring systems. The fractal analysis method of time series is described, which allows finding the Hurst index for use in the developed forecasting models and determining the presence of long-term memory, cyclicity, etc., in the time series. The complex forecasting model includes higher-order exponential smoothing, Holt, Winters, moving average, weighted moving average, and autoregressive models. All the parameters set in these models are related to the Hurst index, which is calculated based on the predictive fractal statistical analysis of the time series. The corresponding descriptions and justifications are given. Using such a model as part of an econometric system will help to more effectively predict and respond to possible changes in the values of pollution parameters. In particular, the persistence of the time series of pollution parameters may mean a stable upward or

downward trend in pollution. Suppose the time series becomes close to random or ergodic. In that case, this may mean an emergency situation or that additional non-permanent emissions have appeared in the region that need to be monitored.

3. Describes a method for monitoring environmental pollution parameters based on a comprehensive model for predicting time series of pollution parameters about statistical fractal analysis. The method considers the results of statistical fractal analysis to determine the direction of the time series trend, which may indicate whether the amount of pollution increases or decreases in the short term. The method also determines the average cycle length based on the V statistic, which establishes the presence of long-term memory in the time series and determines the reliability of the trend forecast calculation. In addition, the Hearst index determines whether emissions of harmful substances, particularly into the air, are stable. In other words, it is shown that if the Hurst index of a time series indicates that the time series is close to random, this means that the environmental situation in the area is unstable and excessive emissions are possible. To ensure environmental safety, local governments and environmental services must respond to this situation. The model for assessing the state of the environment in the monitoring system was improved, which, unlike the known ones, considers the results of comprehensive forecasting of time series of pollution changes and can be a tool for ensuring environmental safety. The model establishes a comprehensive assessment of the state of the environment based on the method of monitoring environmental pollution parameters. The direction of developing an index of the state of the environment, based on the developed methods of monitoring and forecasting time series of pollution and characterized by the consideration of prospective pollution indicators, which can be used in urban environmental monitoring and conditions of environmental uncertainty, has been further developed.

4. Describes the information technology for monitoring environmental pollution parameters, which is distinguished by taking into account the results of analysis and forecasting of changes in pollution parameters and offers an assessment

of the state of the environment, which provides opportunities for quantitative assessment of the environmental situation in the region. Information technology includes methods for collecting information, a method for monitoring environmental pollution parameters, a model for assessing the state of the environment in the monitoring system, a method for calculating the environmental condition index, time series forecasting models, a method for statistical fractal analysis of time series, etc. All of these components allow for a qualitative analysis of the region's environmental situation and predict its future change. 2. The information technology for monitoring pollution parameters based on a monitoring method that uses a comprehensive forecasting model, time series trend prediction, and statistical fractal analysis is verified. The verification was carried out on the example of a time series of environmental pollution parameters in different districts of Beijing, which were recorded from 2013 to 2017. The calculated errors in forecasting and assessing the state of the environment show the effectiveness of the development of such information technology and the relevance of this development for use by the city's environmental services and government agencies. This is important for managing the safety of critical infrastructure facilities, such as chemical plants and energy facilities. A certificate of implementation of the work results within the framework of research projects of Yancheng Polytechnic College was obtained (Appendix A).

REFERENCES

1. Yuanfang, He, Vatskel, Igor, (2019). Problem of evaluation of pollution of the environment. Management of development of complex systems, 37, 168 – 172. https://doi.org/10.6084/m9.figshare.9783230
2. Yuanfang, He, (2019). Fomalization of the problem of evaluation of pollution of the environment. Management of development of complex systems, 38, 168 – 172. https://doi.org/10.6084/m9.figshare.9788702
3. He, Y., Biloshchytskyi, A. O. (2019). Hardware of the information system for environmental pollution monitoring. Scientific Bulletin of Uzhhorod University. Series of Mathematics and Informatics, 2(35), 143–148. https://doi.org/10.24144/2616-7700.2019.2(35).143-148
4. Yuanfang, He (2024). Development of a trend forecasting model for environmental pollution monitoring. Management of development of complex systems, 57, 62 – 66. https://doi.org/10.32347/2412-9933.2024.57.62-66
5. Yuanfang, He. (2020). Formation of requirements for the information system of environmental monitoring. Science Journal Innovation Technologies Transfer. 56-60. https://doi.org/10.36381/iamsti.4.2020.56-60
6. He Yuanfang, Kuchansky, A., Paliy, S. & Shabala, Y. (2021). Problems in Air Quality Monitoring and Assessment, 2021 IEEE International Conference on Smart Information Systems and Technologies *(SIST)*, Nur-Sultan, Kazakhstan, 1-4, https://doi.org/10.1109/SIST50301.2021.9465915
7. Yuanfang, He. (2020). Developing requirements for the information system of environmental monitoring. Seventh international scientific-practical conference «Management of the development of technologies» Topic: "Information technology development of educational content» Kyiv, 25 – 26 March 2020, 129-130. [In Ukrainian]
8. Yuanfang, He. (2019). Concept of information system for monitoring environmental pollution. XV International Scientific and Practical Conference "Project Management in the Development of Society", May 17-18, 2019, 58-59

9. Yuanfang, He. (2019). Monitoring of pollution by analysis traffic on city roads. I International Scientific and Practical Conference IMTCK2019, 61-64.

10. Yuanfang, He. (2019). Participatory sensing for monitoring and forecasting of environmental pollution. VI International Scientific and Practical Conference "Information Technologies and Interactions", December 20, 2019, 95-96.

11. Yuanfang, He. (2018). Participatory sensing for monitoring and forecasting of environmental pollution. V International Scientific and Practical Conference "Information Technologies and Interactions", November 20-21, 2018, 52-53.

12. Jinshui, S., Ming-Huang, W., & Yuh-Shan H. (2012). A historical review and bibliometric analysis of research on estuary pollution. Marine Pollution Bulletin, 64 (1), 13 – 21.

13. Bellinger, Colin, Shazan, Mohomed, Jabbar, Mohomed, Zaiane, Osmar, & Osornio-Vargas, Alvaro. (2017). A systematic review of data mining and machine learning for air pollution epidemiology. doi: 10.1186/s12889-017-4914-3. Retrieved from https://bmcpublichealth.biomedcentral.com/track/pdf/10.1186/s12889-017-4914-3

14. Government expenditure on environmental protection. (2019). Eurostat: Statistics Explained. Retrieved from https://ec.europa.eu/eurostat/statistics-explained/index.php/Government_expenditure_on_environmental_protection

15. Makridakis, S., Wheelwright, S.C., Hyndman, R.J. (2008). Forecasting: methods and applications. John wiley & sons, 656.

16. Kukkonen, J., Partanen, L., Karppinen, A., Ruuskanen, J., Junninen, H., Kolehmainen, M., & et al. (2003). Extensive evaluation of neural network models for the prediction of no 2 and pm 10 concentrations, compared with a deterministic modelling system and measurements in central helsinki. Atmos Environ, 37(32), 4539–550. doi: 10.1016/S1352-2310(03)00583-1

17. Niska, H., Hiltunen, T., Karppinen, A., Ruuskanen, J., Kolehmainen, M. (2004). Evolving the neural network model for forecasting air pollution time series. Eng Appl Artif Intell, 17(2), 159–67. doi: 10.1016/j.engappai.2004.02.002

18. Kolehmainen, M., Martikainen, H., Ruuskanen, J. (2001). Neural networks and periodic components used in air quality forecasting. Atmos Environ, 35(5), 815–25. doi: 10.1016/S1352-2310(00)00385

19. Beckerman, BS., Jerrett, M., Martin, R.V., van Donkelaar, A., Ross, Z., Burnett, R.T. (2013). Application of the deletion/substitution/addition algorithm to selecting land use regression models for interpolating air pollution measurements in california. Atmospheric Environ, 77, 172–177. doi: 10.1016/j.atmosenv.2013.04.024

20. Liu, B.C., Binaykia, A., Chang, P.C., Tiwari, M.K., Tsao, C.C. (2017). Urban air quality forecasting based on multi-dimensional collaborative support vector regression (svr): A case study of beijing-tianjin-shijiazhuang. PLOS ONE, 12(7), 1–17.

21. Bobb, J.F., Valeri, L., Henn, B.C., Christiani, D.C., Wright, R.O., Mazumdar, M., & et al. (2014). Bayesian kernel machine regression for estimating the health effects of multi-pollutant mixtures. Biostatistics, 16(3), 058.

22. Gass, K., Klein, M., Chang, H.H., Flanders, W.D., Strickland, M.J. (2014). Classification and regression trees for epidemiologic research: an air pollution example. Environ Health, 13(1), 17. doi: 10.1186/1476-069X-13-17

23. Kuchansky, A., Biloshchytskyi, A., Andrashko, Yu., Vatskel, V., Biloshchytska, S., Danchenko, O., & et al. (2018). Combined models for forecasting the air pollution level in infocommunication systems for the environment state monitoring. 2018 IEEE 4th International Symposium on Wireless Systems within the International Conferences on Intelligent Data Acquisition and Advanced Computing Systems (IDAACS-SWS). Lviv, 125–130. DOI: 10.1109/IDAACS-SWS.2018.8525608

24. Jia, H., Wang, S., Wei, M., & Zhang, Y. (2011). Scenario analysis of water pollution control in the typical peri-urban river using a coupled hydrodynamic-

water quality model. Frontiers of Environmental Science & Engineering in China, 5(2), 255–265.

25. Bilyuk, P.I., Savenkov, O.I., Trofymchuk, O.M. (2011). Modeling of Pollution and Surface Water in Ukraine. Environmental safety and nature management, 7, 16–34.

26. Trach, Y., Chernyshev, D., Biedunkova, O., Moshynskyi, V., Trach, R., Statnyk, I. (2022). Modeling of Water Quality in West Ukrainian Rivers Based on Fluctuating Asymmetry of the Fish Population. Water 2022, 14, 3511. https://doi.org/10.3390/w14213511

27. Verbesselt J., Hydman R., Newnham G., Culvenor D. (2010). Detecting trend and seasonal changes in satellite image time series. Remote Sensing of Environment. Volume 114, Issue 1, 15 January 2010, 106-115

28. Putrenko, V., Tihohod, V. (2015). Development of geostatistic models of intellectual analysis of air pollution. Eastern-European Journal of Enterprise Technologies, 4/10 (76), 21-26. doi: 10.15587/1729-4061.2015.47889

29. Clark, H. W. (2004). A Practical Geostatistics 2000. Publ. by Geostokos Ecosse, 440.

30. Wackernagel, H. (2003). Multivariate Geostatistics. Springer, 403.

31. Webster, R. (2000). Geostatistics for Environmental Scientists. John Wiley & Sons, 286.

32. Zhang, Z., Yang, W., Zhang, S., Chen, L. (2023). Impacts of Pollutant Emissions from Typical Petrochemical Enterprises on Air Quality in the North China Plain. Atmosphere 2023, 14, 545. https://doi.org/10.3390/atmos14030545

33. Horiachev, H.V., Zhukov, S.O., Skoryna, L.M., & et al. (2011). Automation of reporting in the subsystem "Emissions" of the ASU "Ecoinspeptor" State Inspection of the Ministry of Natural Resources of Ukraine with the help of web-services. Collection of scientific articles of the "III All-Ukrainian Congress of Ecologists with International Participation", Vinnytsia, 1, 150–151. Retrieved from http://eco.com.ua.

34. Xie, X., Semanjski, I., Gautama, S., Tsiligianni, E., Deligiannis, N., Rajan, R.T., Pasveer, F., Philips, W. (2017). A Review of Urban Air Pollution Monitoring and Exposure Assessment Methods. ISPRS Int. J. Geo-Inf., *6*, 389. https://doi.org/10.3390/ijgi6120389

35. Raaschou-Nielsen, O., Andersen, Z.J., Beelen, R., Samoli, E., Stafoggia, M., Weinmayr, G., Hoffmann, B., Fischer, P., Nieuwenhuijsen, M.J., Brunekreef, B. et al. (2013). Air pollution and lung cancer incidence in 17 European cohorts: Prospective analyses from the European Study of Cohorts for Air Pollution Effects (ESCAPE). Lancet Oncol., 14, 813–822.

36. European Commission. (2017). Materials for Clean Air; European Commission: Brussels, Belgium.

37. World Health Organisation. (2017). Data and Statistics; World Health Organisation: Geneva, Switzerland.

38. Kanaroglou, P.S., Jerrett, M., Morrison, J., Beckerman, B., Arain, M.A., Gilbert, N.L., Brook, J.R. (2005). Establishing an air pollution monitoring network for intra-urban population exposure assessment: A location-allocation approach. Atmos. Environ., 39, 2399–2409.

39. Jerrett, M., Buzzelli, M., Burnett, R.T., DeLuca, P.F. (2005). Particulate air pollution, social confounders, and mortality in small areas of an industrial city. Soc. Sci. Med., 60, 2845–2863.

40. Semanjski, I., Bellens, R., Gautama, S., Witlox, F. (2016). Integrating Big Data into a Sustainable Mobility Policy 2.0 Planning Support System. Sustainability, 8, 1142.

41. Semanjski, I., Lopez Aguirre, A.J., De Mol, J., Gautama, S. (2016). Policy 2.0 Platform for Mobile Sensing and Incentivized Targeted Shifts in Mobility Behavior. Sensors, 16, 1035.

42. Gillis, D., Semanjski, I., Lauwers, D. (2016). How to Monitor Sustainable Mobility in Cities? Literature Review in the Frame of Creating a Set of Sustainable Mobility Indicators. Sustainability, 8, 29.

43. Ostro, B.; Sanchez, J.; Aranda, C.; Eskeland, G. (1996). Air pollution and mortality: Results from a study of Santiago, Chile. *J.* Expo. Anal. Environ. Epidemiol., 6, 97–114.

44. Ritz, B.; Wilhelm, M., Zhao, Y. (2006). Air pollution and infant death in southern California, 1989–2000. Pediatrics, 118, 493–502.

45. Miller, K.A., Siscovick, D.S., Sheppard, L., Shepherd, K., Sullivan, J.H., Anderson, G.L., Kaufman, J.D. (2007). Long-term exposure to air pollution and incidence of cardiovascular events in women. N. Engl. J. Med. 447–458.

46. Brauer, M., Lencar, C., Tamburic, L., Koehoorn, M., Demers, P., Karr, C. (2008). A cohort study of traffic-related air pollution impacts on birth outcomes. Environ. Health Perspect., 116, 680.

47. Henderson, S.B., Beckerman, B., Jerrett, M., Brauer, M. (2007). Application of land use regression to estimate long-term concentrations of traffic-related nitrogen oxides and fine particulate matter. Environ. Sci. Technol., 41, 2422–2428.

48. Beckerman, B.S., Jerrett, M., Finkelstein, M., Kanaroglou, P., Brook, J.R., Arain, M.A., Sears, M.R., Stieb, D., Balmes, J., Chapman, K. (2012). The association between chronic exposure to traffic-related air pollution and ischemic heart disease. J. Toxicol. Environ. Health Part A, 75, 402–411.

49. Johnson, M., Isakov, V., Touma, J., Mukerjee, S., Özkaynak, H. (2010). Evaluation of land-use regression models used to predict air quality concentrations in an urban area. Atmos. Environ., 44, 3660–3668.

50. Clougherty, J.E., Wright, R.J., Baxter, L.K., Levy, J.I. (2008). Land use regression modeling of intra-urban residential variability in multiple traffic-related air pollutants. Environ. Health., 7, 17.

51. Brunekreef, B., Beelen, R., Hoek, G., Schouten, L., Bausch-Goldbohm, S., Fischer, P., Armstrong, B., Hughes, E., Jerrett, M., van den Brandt, P. (2009). Effects of long-term exposure to traffic-related air pollution on respiratory and cardiovascular mortality in the Netherlands: The NLCS-AIR study. Res. Rep. (Health Eff. Inst.), 139, 5–71.

52. Beelen, R., Hoek, G., Fischer, P., van den Brandt, P.A., Brunekreef, B. (2007). Estimated long-term outdoor air pollution concentrations in a cohort study. Atmos. Environ., 41, 1343–1358.

53. Kim, S.Y., Sheppard, L., Kim, H. (2009). Health effects of long-term air pollution: Influence of exposure prediction methods. Epidemiology, 20, 442–450.

54. Sahsuvaroglu, T., Jerrett, M., Sears, M.R., McConnell, R., Finkelstein, N., Arain, A., Newbold, B., Burnett, R. (2009). Spatial analysis of air pollution and childhood asthma in Hamilton, Canada: Comparing exposure methods in sensitive subgroups. Environ. Health, 8, 14.

55. Interactive map of monitoring environment of the environment. Retrieved from https://ecomapa.gov.ua.

56. World's Air Pollution: Real-time Air Quality Index. Retrieved from http://waqi.info.

57. Ahmed, A.N., Fazlul Haque, H.M., Rahman, A., Ashraf, M.S., Saha S., Shatabda S. (2017). A Participatory Sensing Framework for Environment Pollution Monitoring and Management. Computers and Society, 1701. 6429.

58. Yi, W., Lo, K., Mak, T., Leung, K., Leung, Y., Meng, M. (2015). A survey of wireless sensor network based air pollution monitoring systems. Sensors, 15(12), 31392-31427.

59. Jong-Won Kwon, Yong-Man Park, Sang-Jun Koo, Hiesik Kim. (2007). Design of air pollution monitoring wystem using ZigBee networks for ubiquitous-city. 2007 International Conference on Convergence Information Technology, 1024-1031.

60. Vasim, K., Ustad, A., Mali, S., Suhas S. Kibile. (2014). Zigbee based wireless air pollution monitoring system using low cost and energy efficient sensors. International Journal of Engineering Trends and Technology, 10/4, 456-460.

61. Rai, A. C., Kumar, P., Pilla, F., Skouloudis, A. N., Di Sabatino, S., Ratti, C., Rickerby, D. (2017). End-user perspective of low-cost sensors for outdoor air pollution monitoring. Science of The Total Environment, 607, 691-705.

62. Son, M., Cho, D. G., Lim, J. H., Park, J., Hong, S., Ko, H. J., Park, T. H. (2015). Real-time monitoring of geosmin and 2-methylisoborneol, representative odor compounds in water pollution using bioelectronic nose with human-like performance. Biosensors and Bioelectronics, 74, 199-206.

63. Xue, X. Y., Cheng, R., Shi, L., Ma, Z., Zheng, X. (2017). Nanomaterials for water pollution monitoring and remediation. Environmental chemistry letters, 15(1), 23-27.

64. Meyer, A. M., Klein, C., Fünfrocken, E., Kautenburger, R., Beck, H. P. (2019). Real-time monitoring of water quality to identify pollution pathways in small and middle scale rivers. Science of The Total Environment, 651, 2323-2333.

65. Wernersson, A. S., Carere, M., Maggi, C., Tusil, P., Soldan, P., James, A., & et al. (2015). The European technical report on aquatic effect-based monitoring tools under the water framework directive. Environmental Sciences Europe, 27(1), 7.

66. Qu, C., Shi, W., Guo, J., Fang, B., Wang, S., Giesy, J. P., & et al. (2016). China's soil pollution control: choices and challenges. Environmantal Science & Technology, 50/24,13181-13183.

67. Sueoka, Y., Sakakibara, M., Sano, S., Yamamoto, Y. (2016). A new method of environmental assessment and monitoring of Cu, Zn, As, and Pb pollution in surface soil using terricolous fruticose lichens. Environments, 3(4), 35.

68. Karl, H., Willig, A. (2005). Protocols and Architectures for Wireless Sensor Networks, John Wiley and Sons Ltd, The Atrium, Southern Gate, Chichester, West Sussex, England, 2005.

69. Culler, D. Estrin, D., Srivastava, M. (2004). Overview of Sensor Networks, IEEE Computer, August 2004.

70. Martinez, K., Hart, J. K., Ong, R. (2004). Environmental sensor networks", IEEE Computer Journal, Vol. 37 (8), 50-56, August 2004.

71. Mainwaring, A., Culler, D., Polastre, J., Szewczyk, R., Anderson, J. (2002). Wireless sensor networks for habitat monitoring", Proceedings of the 1st

ACM International workshop on Wireless sensor networks and applications, Atlanta, Georgia, USA, 88-97, 2002.

72. Akyildiz, I. F., Pompili, D., Melodia, T. (2005). Underwater acoustic sensor networks: research challenges, Ad Hoc Networks, Vol. 3 (3), 257-279, May 2005.

73. Ma, Y., Richards, M., Ghanem, M., Guo Y., Hassard, J. (2008). Air Pollution Monitoring and Mining Based on Sensor Grid in London, Sensors 2008, Vol. 8(6), 3601-3623.

74. Hassard, G., Ghanem, M., Guo, M., Hassard, J., Osmond, M., Richards, M. (2004). Sensor Grids For Air Pollution Monitoring", in the Proceedings of 3rd UK e-Science All Hands Meeting, 2004.

75. Khemapech, I., Duncan, I., Miller, A. (2005). A survey of wireless sensor networks technology. in PGNET, In the Proceedings of the 6th Annual Postgraduate Symposium on the Convergence of Telecommunications, Networking & Broadcasting , Liverpool, UK, EPSRC, June 2005.

76. Warneke, B., Pister, K.S.J. (2002). MEMS for Distributed Wireless Sensor Networks. 9th International Conference on Electronics, Circuits and Systems, Croatia, September 2002.

77. Son, B., Her, Y., Kim, J. (2006). A design and implementation of forest-fires surveillance system based on wireless sensor networks for South Korea mountains", International Journal of Computer Science and Network Security (IJCSNS), 6, 9, 124–130.

78. ALERT, Available from: http://www.alertsystems.org/, Accessed on: 14 August 2009.

79. Keitt, T.H., Urban D.L., Milne, B.T. (1997). Detecting critical scales in fragmented landscapes. Conservation Ecology(online), Vol. 1.

80. Heidemann, J. et al. (2005). Underwater Sensor Networking: Research Challenges and Potential Applications," USC/ISI tech. rep. ISI-TR-2005-603.

81. Akyildiz, I. F., Su, W., Sankarasubramaniam, Y., Cayirci, E. (2002). Wireless Sensor Networks: A Survey, Elservier Computer Networks, Vol.38 (4), pp. 393-422, March 2002.

82. Hill J., Culler. D. (2002). A wireless embedded sensor architecture for system-level optimization. In UC Berkeley Technical Report.

83. Zhang X, Wang Y, Niu T, Zhang X, Gong S, Zhang Y, Sun J. (2012). Atmospheric aerosol compositions in China: spatial/temporal variability, chemical signature, regional haze distribution and comparisons with global aerosols. Atmos. Chem. Phys. 12, 779–799. doi:10.5194/acp-12-779-2012

84. Guo S, et al. (2014). Elucidating severe urban haze formation in China. Proc. Natl Acad. Sci. USA 111, 17 373–17 378. doi:10.1073/pnas.1419604111

85. Liang X, Li S, Zhang S, Huang H, Chen SX. (2016). PM2.5 data reliability, consistency, and air quality assessment in five Chinese cities. J. Geophys. Res. Atmos. 121, 10 220–10 236. doi:10.1002/2016JD024877

86. Huang K, Zhuang G, Wang Q, Fu J, Lin Y, Liu T, Han L, Deng C. (2014). Extreme haze pollution in Beijing during January 2013: chemical characteristics, formation mechanism and role of fog processing. Atmos. Chem. Phys. Discuss. 14, 7517–7556. doi:10.5194/acpd-14-7517-2014

87. Wang L, Zhang N, Liu Z, Sun Y, Ji D, Wang Y. (2014). The influence of climate factors, meteorological conditions, and boundary-layer structure on severe haze pollution in the Beijing-Tianjin-Hebei region during January 2013. Adv. Meteorol. 685971. doi:10.1155/2014/685971

88. Zhang R, Wang G, Guo S, Zamora ML, Ying Q, Lin Y, Wang W, Hu M, Wang Y. (2015). Formation of urban fine particulate matter. Chem. Rev. 115, 3803–3855. doi:10.1021/acs.chemrev.5b00067

89. Shuyi Zhang, Bin Guo, Anlan Dong, Jing He, Ziping Xu, Song Xi Chen. (2017). Cautionary tales on air-quality improvement in Beijing. Proc Math Phys Eng Sci. 473(2205): 20170457. doi: 10.1098/rspa.2017.0457

90. Keogh, E., Pazzani, M. (1998). An enhanced representation of time series which allows fast and accurate classification, clustering and relevance

feedback. 4th Int'l Conference on Knowledge Discovery and Data Mining. – New York, 239–241.

91. Singh S. (2000). Pattern Modeling in Time-Series Forecasting. Cybernetics and Systems. An International Journal. 31, no. 1. 49–65.

92. Ratanamahatana C.A. (2005). Mining time series data. Data Mining and Knowledge Discovery Handbook: A Complete Guide for Practitioners and Researchers. – Kluwer Academic Publishers, 36 p.

93. Stevenson William J. (1985). Business statistics: concept and application. New York: Harper & Row, 2nd ed., 637 p.

94. Stock J., Watson M. (2007). Introduction to Econometrics. 2nd edition. Addison Wesley, 840 p.

95. Parzen E. (2004). Long memory of statistical time series modeling NBER-NSF Time Series Confrence-2004. – Texas, 10 p.

96. Velleman P.F., Hoagin D.C. (1981). Applications, basics and computing of exploratory data analysis. Boston: Duxbury Press, 1981. – 356 p.

97. Box G.E.P., Jenkins G.M. (1976). Time series analysis: forecasting and control. San Francisco: Holden-Day, 575 p.

98. Barbulescu A., Bautu E. (2009). Time Series Modeling Using an Adaptive Gene Expression Programming Algorithm. International Journal of Mathematics and Computation. Vol. 3, Issue 2. – P. 85–93.

99. Mandelbrot B.B. (1971). When can price be arbitraged efficiently? A limit to the validity of the random walk and martingale. Models Review of Economics and Statistics. 53 (3). 225–236.

100. Mandelbrot B.B. (1972). Statistical methodology for non-periodic cycles: from the covariance to R/S analysis. Annals of Economic and Social Measurement. 1. 259–290.

101. Mandelbrot B.B., Hudson R.L. (2004). The (mis)behavior of markets: a fractal view of risk, ruin and reward. New York: Basic Books, 328 p.

102. Hurst H.E. (1951). Long-term storage capacity of reservoirs. Transactions of the American Society of Civil Engineers. 116. 770–799.

103. Williams B. (1998). Trading chaos. Applying expert techniques to maximize your profit. New York: John Wiley & Sons Inc, 307 p.

104. Parzen E. (2004). Long memory of statistical time series modeling NBER-NSF Time Series Confrence-2004. Texas, 2004. 10 p.

105. Anis A., Lloyd E. (1976). The expected value of the adjusted rescaled Hurst Range of independent normal summands. Biometrika. 63. 111–116.

106. Peters E. E. (1994). Fractal market analysis: applying chaos theory to investment and economics. John Wiley & Sons Inc, 336 p.

107. Brown Robert G. (1959). Statistical forecasting for inventory control. – US: McGraw-Hill Inc., 223 p.

108. Holt Charles C. (1957). Forecasting trends and seasonal by exponentially weighted averages. International Journal of Forecasting. Vol. 20, no.1. – P. 5–10.

109. Vercellis Carlo. (2009). Business intelligence: data mining and optimization for decision making. Cornwall: John Wiley & Sons Ltd. Publication, 2009. 417 p.

110. Zhang, S., Guo, B., Dong, A., He, J., Xu, Z. Chen, S.X. (2017) Cautionary Tales on Air-Quality Improvement in Beijing. Proceedings of the Royal Society A, Volume 473, No. 2205, Pages 20170457.

APPENDIX A. ACT OF IMPLEMENTATION

盐城工业职业技术学院
Yancheng Polytechnic College

ACT OF IMPLEMENTATION

The act of implementing the results of the dissertation work of PhD student He Yuanfang

INFORMATION TECHNOLOGY OF THE ENVIRONMENTAL POLLUTION MONITORING BASED ON TREND FORECASTING MODELS

The commission considered in detail the results of He Yuanfang's dissertation research, **"INFORMATION TECHNOLOGY OF THE ENVIRONMENTAL POLLUTION MONITORING BASED ON TREND FORECASTING MODELS"** and established:

1. He Yuanfang has been actively cooperating with our company for the past few years, especially on his dissertation research topic. The commission believes that He Yuanfangs's dissertation research has essential significance and practical interest for environmental air quality monitoring in the People's Republic of China. This will improve the quality of life and comfort of state citizens.
2. Developed methods and models of air quality monitoring and information technology are also essential tools for local authorities and environmental services to check compliance with environmental requirements by factories and industries that may emit air pollutants.
3. Air quality monitoring methods and models are relevant to different groups of interested persons and organizations: the public, health care institutions, law enforcement agencies, manufacturing companies and industry, government and local authorities, who can use air quality monitoring data to develop and implementation of effective strategies to reduce air pollution and protect public health.

The decision of the commission:

Information technology, methods, and models of pollution monitoring, developed by He Yuanfang and part of his dissertation work **"INFORMATION TECHNOLOGY OF THE ENVIRONMENTAL POLLUTION MONITORING BASED ON TREND FORECASTING MODELS"** offer a powerful toolkit for practical pollution monitoring, which is very relevant in the People's Republic of China. The committee members believe that He Yuanfang deserves to be awarded a Ph.D. in Information Systems and Technologies.

12/27/2023

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APPENDIX B. LIST OF THE APPLICANT'S PUBLICATIONS ON THE THEME OF THE DISSERTATION AND INFORMATION ON THE APPROVAL OF THE RESULTS OF THE DISSERTATION

Articles in professional publications of Ukraine
(included in the list of the Ministry of Education and Science of Ukraine)

1. **Yuanfang, He, & Vatskel, Igor,** (2019). Problem of evaluation of pollution of the environment. Management of development of complex systems, 37, 168 – 172. [category «B»] https://doi.org/10.6084/m9.figshare.9783230 https://urss.knuba.edu.ua/files/zbirnyk-37/29.pdf
2. **Yuanfang, He,** (2019). Fomalization of the problem of evaluation of pollution of the environment. Management of development of complex systems, 38, 168 – 172. [category «B»] https://doi.org/10.6084/m9.figshare.9788702 https://urss.knuba.edu.ua/files/zbirnyk-38/28.pdf
3. **He, Y., & Biloshchytskyi, A. O.** (2019). Hardware of the information system for environmental pollution monitoring. Scientific Bulletin of Uzhhorod University. Series of Mathematics and Informatics, 2(35), 143–148. [category «B»] https://doi.org/10.24144/2616-7700.2019.2(35).143-148 http://visnyk-math.uzhnu.edu.ua/article/view/189498/188916
4. **Yuanfang, He** (2024). Development of a trend forecasting model for environmental pollution monitoring. Management of development of complex systems, 57, 62 – 66. [category «B»] https://doi.org/10.32347/2412-9933.2024.57.62-66

Articles in professional publications of Ukraine
(not included in the list of the Ministry of Education and Science of Ukraine)

Yuanfang, He. (2020). Formation of requirements for the information system of environmental monitoring. Science Journal Innovation Technologies Transfer. 56-60. https://doi.org/10.36381/iamsti.4.2020.56-60

Approbation works

1. **He, Y., Kuchansky, A., Paliy, S. & Shabala, Y.** (2021). Problems in Air Quality Monitoring and Assessment, 2021 IEEE International Conference on Smart Information Systems and Technologies (SIST), Nur-Sultan, Kazakhstan, 1-4, https://doi.org/10.1109/SIST50301.2021.9465915 [**Scopus, Web of Science**]

2. **Yuanfang, He.** (2020). Developing requirements for the information system of environmental monitoring. Seventh international scientific-practical conference «Management of the development of technologies» Topic: "Information technology development of educational content» Kyiv, 25 – 26 March 2020, 129-130. [In Ukrainian]

3. **Yuanfang, He.** (2019). Concept of information system for monitoring environmental pollution. XV International Scientific and Practical Conference "Project Management in the Development of Society", May 17-18, 2019, 58-59

4. **Yuanfang, He.** (2019). Monitoring of pollution by analysis traffic on city roads. I International Scientific and Practical Conference IMTCK2019, 61-64.

5. **Yuanfang, He.** (2019). Participatory sensing for monitoring and forecasting of environmental pollution. VI International Scientific and Practical Conference "Information Technologies and Interactions", December 20, 2019, 95-96.

6. **Yuanfang, He.** (2018). Participatory sensing for monitoring and forecasting of environmental pollution. V International Scientific and Practical Conference "Information Technologies and Interactions", November 20-21, 2018, 52-53.