TRANS-URBAN-EU-CHINA
Transition towards urban sustainability through socially integrative cities in the EU and in China

Deliverable 4.3

Report with recommendations on Big Data Technologies, Analytics Solutions, and Analytics Results, and on the Creation of a Community of Communities to enable Holistic Sustainable Urban Planning

WP 4: Integrated Transition Pathways towards Sustainable Urban Planning and Governance

Task 4.3: The Digital Transition in Urban Governance and Planning

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Lead author(s):	WU Zhiqiang (CIUC) CAO Buyang (CIUC) Otthein HERZOG (CIUC) Edna PASHER (ISCI) Lee Shamir (ISCI) Annemie Wyckmans (NTNU)
Reviewers:	Nikolaos KONTINAKIS (EUR) LIU Jian (THSA)

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Executive Summary

This Deliverable 4.3 reports on the results of Task 4.3 on “Recommendations on Big Data Technologies, Analytics Solutions, and Analytics Results, and on the Creation of a Community of Communities to enable Holistic Sustainable Urban Planning” for socially inclusive cities.

Air quality is an important aspect of a socially inclusive city as it influences the quality of life, e.g., the health of the people in general[1] in a city by the distance of living quarters to busy roads and/or industry conglomerates. A recent research preprint[2] demonstrates that even small increases in fine particulate matter (PM2.5) have had an outsized effect in the US, and that an increase of 1 microgram/m^3 corresponded to a 15% increase in Covid-19 deaths. This result is supported by another recent preprint[3] where current SARS-CoV-2 cases and deaths recorded for several sites across England were compared with public databases to both regional and sub-regional air pollution data. The levels of nitrogen oxides and sulphur dioxide as markers of poor air quality are associated with increased numbers of COVID-19-related deaths across England. They could show also, that particulate matter contributes to increased infectivity, and they also analysed the relative contributions of individual fossil fuel sources on key air pollutant levels and found out that the levels of some air pollutants are linked to COVID-19 cases and adverse outcomes. In this report, we explore the interrelationships of air quality, industrial entities, daily-life activities, and transportation with annual, monthly and real-time data. It could be determined how the urban air quality is correlated with urban size, population, industrial infrastructures, shopping centres, and transportation facilities.

The results of the Big Data Analytics of the contributing factors are presented in respect to air pollution and transport based on multiple data sources for Urban Living Labs in China (Tianjin, Baoding, Wuhan, and Jingdezhen). Various impacting factors are taken into account during the analyses: Monthly and real-time air quality data, concentrations of gaseous pollutants and fine particle (AQI (Air Quality Index) measured by NO_2, O_3, SO_2, CO, $PM_{2.5}$, PM_{10}), derived from the Platform for AQI Intelligent Management[4]. The monthly air quality data for the ULLs ranges from December 2013 to April 2020.

The annual transportation data ranging from 2013 to 2019 are collected from the National and Local Statistical Yearbooks. Furthermore, the locations of industrial Points of Interest (PoIs) of construction, machinery and electronics, chemical and metallurgy, mining, and factories as well as shopping areas in the ULLs are derived from AMap[5]. Real-time traffic data of Tianjin and Wuhan are obtained from AMap for the same period as the real-time air quality data.

The analysis methods used include Big Data Analytics for non-conventional data and concentrate on

- Visualization of some data to determine the variations of real-world data over time,
- Correlation analysis to determine the interdependencies between data,
- Non-parametric tests to determine similarity and class membership of city-specific environmental data.

[1] https://www.who.int/airpollution/ambient/health-impacts/en/
[2] Xiao Wu et al. (2020). Exposure to air pollution and COVID-19 mortality in the United States: A nationwide cross-sectional study. medRxiv 2020.04.05.20054502; DOI: https://doi.org/10.1101/2020.04.05.20054502.
[3] Marco Travaglio et al. (2020). Links between air pollution and COVID-19 in England. medRxiv 2020.04.16.20067405; doi: https://doi.org/10.1101/2020.04.16.20067405
[4] PALM at www.zq12369.com
[5] m.amap.com

These use of the non-parametric tests allows for analysing a group of cities with similar characteristics, i.e., with the same distribution of the values of public transport construction indicators, instead of individual cities. This result leads to improved analytical efficiency, as cities can be classified according to the public transport construction indicators, and only a representative of each class needs to be be analysed in-depth

In addition, Deep Learning Neural Network Technologies were applied in order to develop a BPNN model for Air Quality Index prediction in cities. It delivers satisfactory predictions of the AQI based on a data set of road properties, traffic, and weather data.

These data analyses constitute a top-down evidence-based framework for testing, monitoring, benchmarking, and assessing impacts of the urban transition in China.

In addition to this computational approach, we present the benefits of communities and especially online communities to support the city stakeholders to make a city smarter by engaging them.

Some practical examples from the CoC (Community of Communities) online platform illustrate and demonstrate how communities can serve decision makers and how to use them wisely to create a win-win situation. The Tel Aviv DigiTel example is described as a very successful example of a win-win situation for citizens and the municipality.

The main conclusion from this bottom-up approach is the importance of collaborations to achieve real success, namely the collaboration between decision makers and residents, between experts and stakeholders, and the recognition of the interrelationships of a community to drive change and generate innovation together. This approach complements and is supported by the evidence-based Big Data Analysis of the real-time and historical data and by appropriate computational models for the prediction of the corresponding city properties according to (future) planning decisions.

Thus the combination of data-based computational and human interaction models represents the ultimate combination for holistic and sustainable urban planning, as pursued and demonstrated in this TRANS URBAN EU-China project. The insights gained through the data analyses and the online CoC platform provide a solid base for decision-making to facilitate sustainable development and thus partially paving the way for the digital transformation into socially integrative cities that are defined as[6] “socially mixed, cohesive, liveable and vibrant. Compactness, functional mix, and intra-urban connectivity as well as equal rights regarding the access to municipal services play an important role. Environmental quality, the quality of public spaces and the quality of life contribute to the well-being of the population. Strengthening a sense of community and fostering a sense of place as well as pre-serving cultural heritage shape the city’s in- and outward-bound image. Investments into neigh-bourhood improvement, service delivery, infrastructure and the quality of housing are important supportive measures. Empowerment and participation of the population, as well as social capital, are indispensable.”

In this context, local governments are able to use the results of the digital transition concerning transportation and the environment to decide on improvements: based on monitoring air pollution and traffic by using Big Data Analytics and learned air pollution prediction models they are able to set up new strategies to avoid traffic jams and to reduce air pollution based on “cold” evidence.

[6] TRANS-URBAN-EU-CHINA Deliverable D 6.6 Workshop Report on “Theoretical aspects of transition towards urban sustainability and the role of socially integrative cities”, p.1

1. Objectives of Subtasks 4.3.2 and 4.3.3

In a first report, the results of the Subtask 4.3.1 of the TRANS URBAN EU-China project were reported on the specification and setup of a system for Big Data Analytics and the online Community of Communities system. According to the project Description of Work, this deliverable covers the objectives of subtask 4.3.2 and 4.3.3:

a. Identify the digital transition components starting from Big Data analysis and citizen's contributions in Living Labs in China for initiating and creating socially integrative cities and facilitating sustainable development in order to support testing, monitoring, benchmarking and assessing impact for promising pathways, services, technologies and scenarios in Task 5.1.
b. Develop effective pathways on how to use
- data-driven Decision Support Systems at different governance levels (local to regional) and
- stakeholder participation for creating socially integrative communities.
The Chinese Living Lab cities will provide open data to build Decision Support Systems based on Big Data analysis.
c. Provide differentiated transformative knowledge to support urban governance and planning for the Living Lab cities in China through a Decision Support Platform with the following features:
- Descriptive: providing data visualization to present the urban status.
- Diagnostic: support for urban diagnostics via supervised learning techniques, e.g., by comparing the environmental data for two cities.
- Predictive: simulations can be run in the platform to validate the gained transformative knowledge, e.g., using infrastructure data (static) and real time traffic data (dynamic) to forecast the traffic status in a certain area at a certain time and its impacts.
- Prescriptive: data, mathematical models, and algorithms in the platform will provide rationale suggestions based upon the outcomes of diagnostics and/or simulation.
d. Perform Big Data analytics with an existing system at the CIUC. Its results will be an evidence-based foundation for an extended communication and cooperation process between urban authorities and citizens, and other stakeholders.
e. Create an online 'Community of Communities' to cover the social aspect, inspired by the online platform 'Knowledge Board' that will serve as an online "one stop shop" platform for all stakeholders. This will allow for knowledge sharing and knowledge creation across borders in online Living Labs where real estate developers, policy makers and citizens can e-meet, share insights and expectations, post and rank ideas for new joint projects and capitalize on lessons learnt from past projects.

This Deliverable - D4.3 reports on "Recommendations on Big Data Technologies, Analytics Solutions, and Analytics Results, and on the Creation of a Community of Communities to enable Holistic Sustainable Urban Planning". First, it describes the basic technologies for data generation and collection, and describes Big Data and AI technologies applied to city data. In the next section,. The CoC is discussed and the experiences gained are documented by recommendations.
The remaining part of this report is devoted to the analysis of the interrelationships between air pollution/air quality and transport for four Chinese Cities and a prediction model for the Air Quality Index. Finally, some conclusions are discussed that were gained through the work of the CIUC and ISCI teams.

2. Basic Technologies for Data Generation and Collection in Cities

The evolution of the IoT (Internet of Things) allows to overcome the classical limitations of the Internet in connecting the web with the real world. The IoT offers a variety of innovative technological features, ranging from embedded systems and linked sensors development (CyberPhysical Systems) to the application of intelligent systems to communications protocols [1].

Urban environments in Europe and China are experiencing a digitalisation through sensorification and datafication brought about by the massive application of sensor technologies and mobile platforms. Accordingly, both the Big Data Analytics Framework - specifically addressing air pollution, transport and mobility, and data sharing for inter-municipal cooperation -, and the Community of Communities (CoC) platform (together with the data analytics system) are designed to become prominent contributors to urban digitalisation strategies. These two efforts combine an evidence-based top-down approach (Big Data Analytics) with a bottom-up approach (contributions of citizens in the CoC) that together can be used to plan for improvements supported by all stakeholders.

Artificial Intelligence (AI) technologies are a prominent contributor to the urban digitalisation development for the next decades. This transition to the digitalisation is driven by the IoT and enabled by Big Data technologies, a field of AI empowering city administrations to base decisions on measurable evidence. Using Big Data and IoT technologies, city administrations are able to

- collect large amounts of data that are being generated, e.g., by transportation or air pollution monitoring devices in a city,
- identify patterns in the data that reveal the actual status as well as the effects of the transportation, such as air pollution, and their development over time,
- identify the different causes of air pollution and their contributing effects,
- predict the degree of air pollution over time.

Decision processes in the field of environment are crucial for the success of urban transition strategies. They require an accurate understanding of environmental phenomena, including risks and impacts. Novel information and communication technologies (ICT) are able to provide useful tools to achieve this goal [2], [3].

Focusing on strategies at the local level, local governments are able to use the results of the digital transition concerning transportation and the environment to decide on improvements: based on monitoring air pollution and traffic. They are able to set up new strategies to avoid traffic jams and to reduce air pollution based on "cold" evidence.

The following sections demonstrate how Big Data and AI technologies with descriptive, diagnostic, and predictive features and the contributions by citizens can provide a pathway to data-driven decision support and stakeholder participation for the two selected investigation areas: environmental issues with the example of air pollution (for both the regional and cross-regional scale), and transportation in Chinese Urban Living Labs (ULLs) Tianjin, Baoding, Wuhan, and Jingdezhen.

It should be noted here that the Covid-19 pandemic made it impossible to get into personal contact with the administrations of these cities during 2020. However, as the online data collections were not interrupted, it was possible to streamline the tasks using only the data available in the Internet.

3. Big Data and AI Technologies for City Data

Data-driven decision and policy making is a currently observable in both Chinese and European cities [4], as data sharing is expected to encourage citizens to engage actively in decision making and political activities [5], [6]. In order to effectively foster citizens' participation in decision and plan making, the reference system featuring information integration and effective planning operation for planners must first be established, as a prerequisite for further opening up to the public. To this end, the CIUC developed a Big Data platform including a variety of open data for intelligent city applications that notably address air pollution, transportation, and data sharing for inter-municipal cooperation:

This Big Data Analytics platform supports the objectives of Task 4.3 by Information data classification and screening management, trend prediction, data intelligence analysis and visualization. Pan et al. [3] define urban Big Data and its applications to China's city intelligence. The CIUC Big Data Analytics platform provides intelligent urbanization data support with reliable mathematical assistance for scientific research and policy-making in the three fields

- intelligent diagnosis,
- intelligent planning, and
- intelligent governance of urbanization development (Figure 1).

This intelligent urbanization data support platform provides reliable mathematical assistance for scientific research and policy-making in the three fields of intelligent diagnosis, intelligent planning and intelligent governance of urbanization development, and it has been used for the work of Task 4.3.

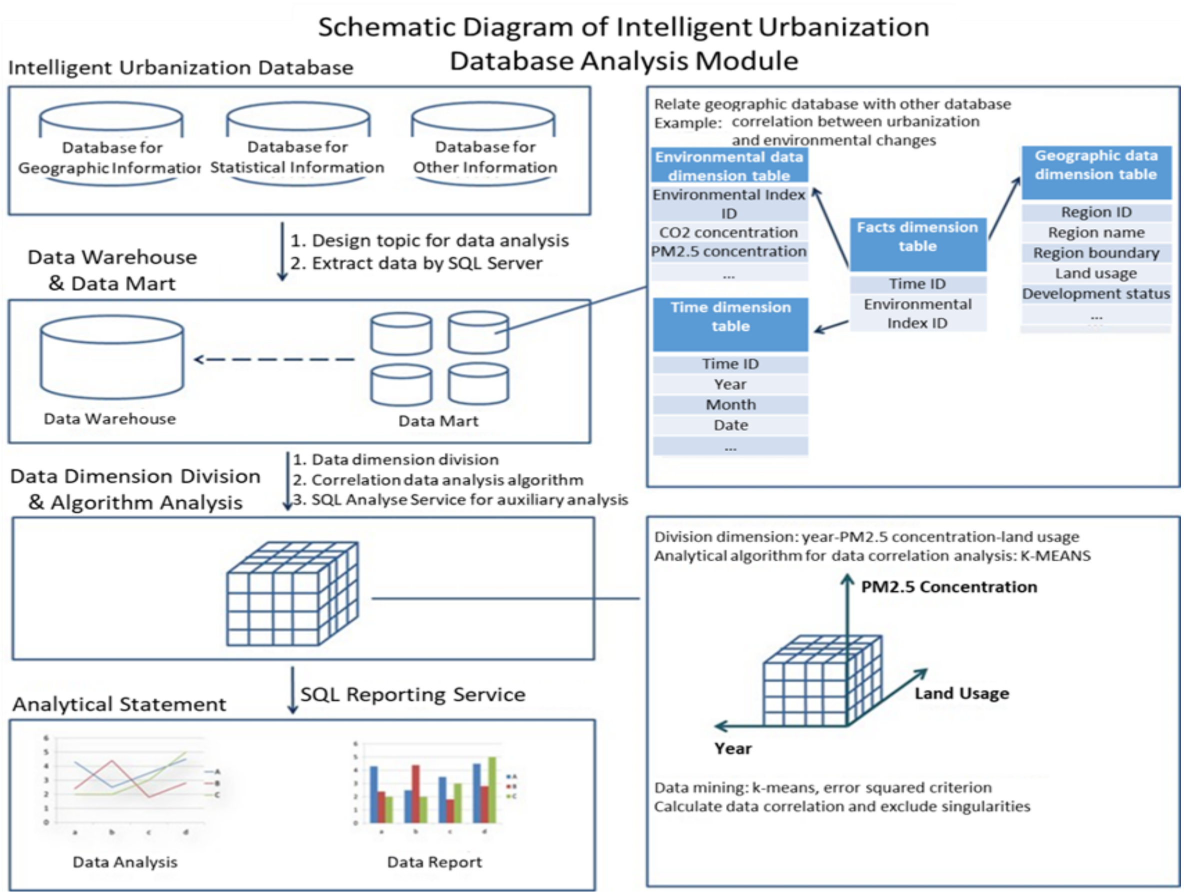

Figure 1 Intelligent Urbanization Database Analysis Modules

This database analysis module is composed of four parts, each corresponding to primary data collection (first part - Intelligent Urbanization Database), data filtration and reprocessing (second part – Data Warehouse & Data Mart), data processing and analysis (third part – Data Dimension Division & Algorithm Analysis), and analysis report (fourth part – Analytical Statement). The design of the system supports both data flow and the corresponding analysis; therefore its flexibility is able to meet various demands generated during planning work.
The platform provides assistance for urban and rural planning through integration and sharing of local urbanization development data obtained during the process of local service establishment.
The data sharing system allows for analysing the different needs for urban and rural planning and collects various pieces of information in real-time. In this work, we concentrated on transportation and air pollution measured by the Air Quality Index (AQI), real-time data as well as GIS and Point-of-Interest (PoI) data. The real-time data of these dimensions are collected and organized, establishing a non-conventional database. The system provides the corresponding functions such as data query, browsing and downloading for planners to meet their needs.

Based on these available systems and data sources, the CIUC adapted and expanded the available platforms and the databases in order to satisfy the additional needs of the TRANS URBAN project, e.g., by providing additional data from four ULLs and new functionalities, e.g., for regression analysis, and additional history as well as real-time data from four ULLs:

- The database was expanded to store the datasets needed by the project, e.g., by the datasets purchased from Oxford Economics including economic and social data, and providing also historic as well as prognosis information. They are necessary to conduct city analyses (also over time) and to create the corresponding reports. The datasets are centrally stored and managed through the ArcGIS portal. They can be shared between partners upon request with the proper privileges.
- More functions were developed to accommodate the needs of the project including data analysis (e.g., traffic, air pollution). The traffic flow can be analysed by using the embedded Big Data analysis tools to reveal the traffic patterns within a city. The outcome was used to diagnose issues in urban development.
- The underlying architecture was enhanced to enable the communication between the CIUC and the CoC platform, in order to provide the necessary data transfer and analysis result information exchange. The data collected by the CoC platform was transferred to the CIUC Big Data platform, where it was analysed and visualized.

One of the major functions of the Big Data platform is to acquire real-time air quality data automatically and to provide the tools to view, analyse, and report on it [7]. The analytical outcome can provide municipal administrations with the information needed to make decisions for reducing air pollution, and increasing the quality of life for the residents affected by air pollution. An example of real time air pollution (PM 2.5) visualisation is depicted in Figure 2. This is a prominent example where an improvement of the PM 2.5 in the air will also avoid a string of severe health impacts[7]:
"An estimated 4.2 million premature deaths globally are linked to ambient air pollution, mainly from heart disease, stroke, chronic obstructive pulmonary disease, lung cancer, and acute respiratory infections in children. Worldwide ambient air pollution accounts for:

- 29% of all deaths and disease from lung cancer
- 17% of all deaths and disease from acute lower respiratory infection

[7] https://www.who.int/airpollution/ambient/health-impacts/en/

- 24% of all deaths from stroke
- 25% of all deaths and disease from ischaemic heart disease
- 43% of all deaths and disease from chronic obstructive pulmonary disease
- Pollutants with the strongest evidence for public health concern, include particulate matter (PM), ozone (O3), nitrogen dioxide (NO2) and sulphur dioxide (SO2)."

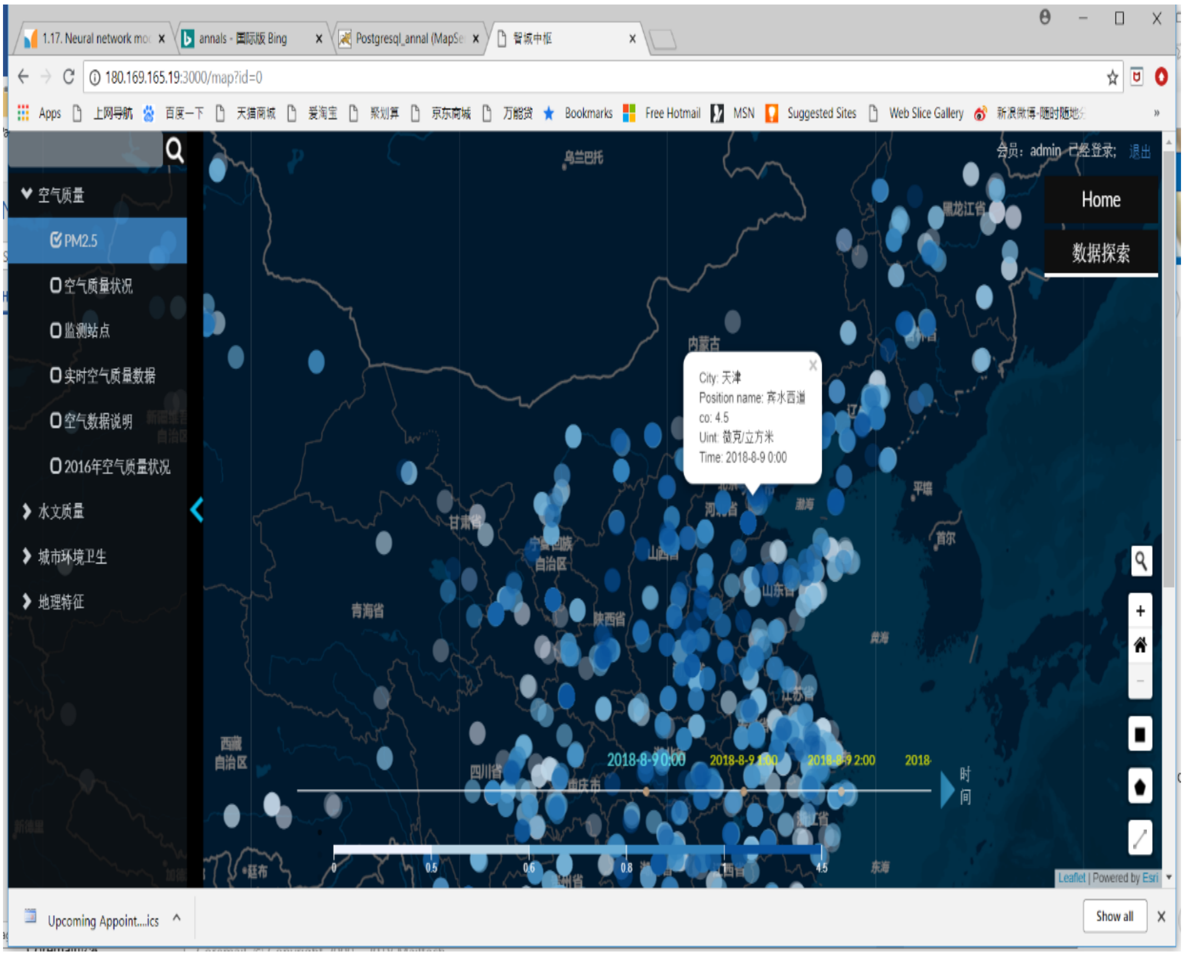

Figure 2 Overlay of environmental data on the Big Data analytics platform

This description is corroborated by the analysis of the influence of air pollution during the current COVID-19 pandemic: A recent study published as preprint [8] found that even small increases in fine particulate matter (PM2.5) have had an outsized effect in US cities: an increase of 1 microgram/m3 corresponded to a 15% increase in Covid-19 deaths. This result is supported by [9] who compared current SARS-CoV-2 cases and deaths recorded for several sites across England with public databases to both regional and sub-regional air pollution data. The levels of nitrogen oxides and sulphur dioxide as markers of poor air quality are associated with increased numbers of COVID-19-related deaths across England. They could show also, that particulate matter contributes to increased infectivity, and they also analysed the relative contributions of individual fossil fuel sources on key air pollutant levels and found out that the levels of some air pollutants are linked to COVID-19 cases and adverse outcomes.

The Big Data platform allows also for analysing traffic situations for a certain area, for pinpointing traffic problems, e.g., to identify infrastructure bottlenecks, unreasonable traffic light settings, or hot spots during the rush hours. The data related to transportation can be viewed, analysed, and reported. The data can also be shared with team members to enable collaborative decision making. One of the data usages is to predict traffic status (light, normal, congested) of a street block and can be visualized on the map. During peak hours and regular hours, the traffic patterns can be different.

The Origin-Destination analysis can be used by transport planners as an input for transport models. The following diagrams illustrate traffic analyses based on taxi data stored in the application (hot spots and Origin-Destination analysis) in **Error! Reference source not found.** and 4.

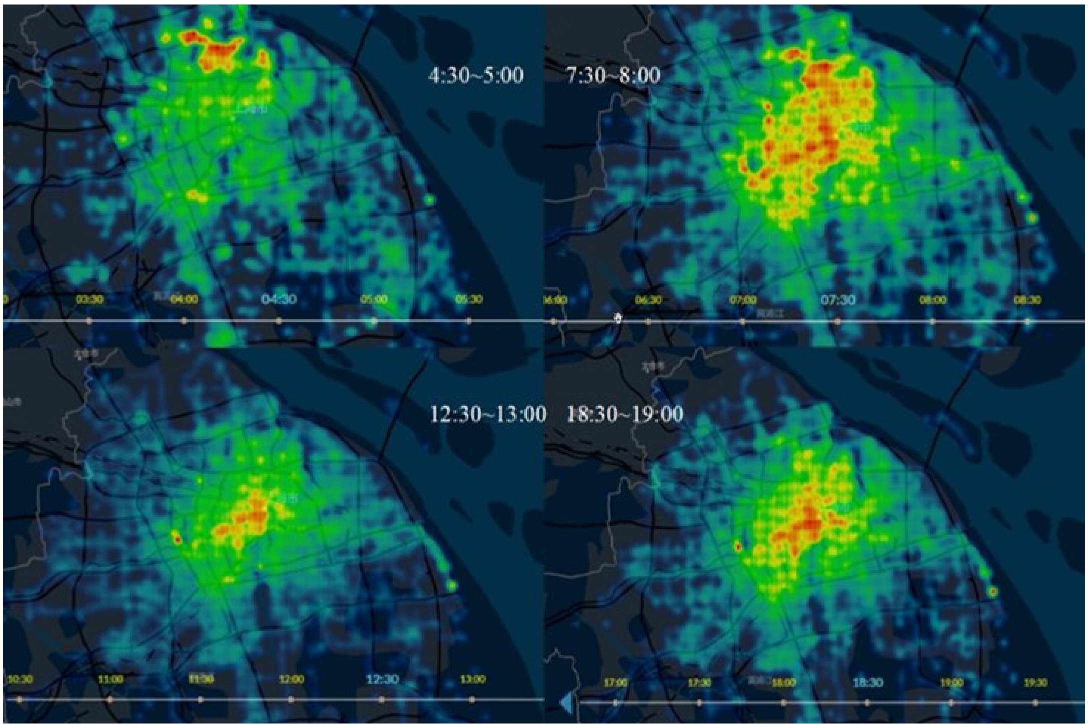

Figure 3 Overlay of traffic hot spot on the Big Data analytics platform

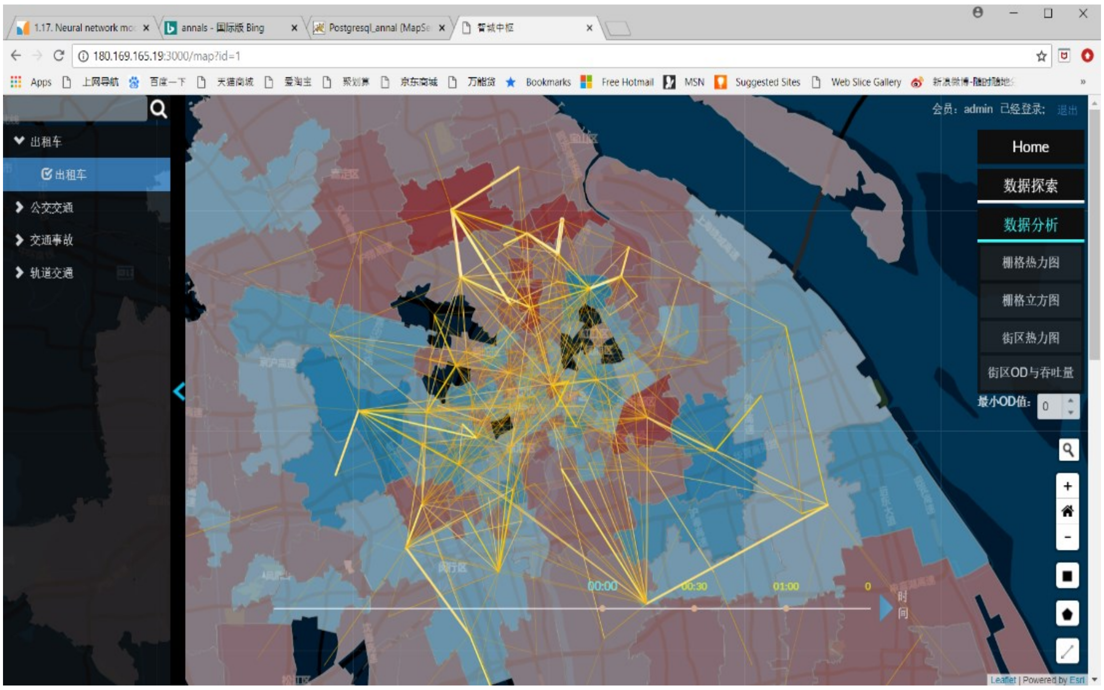

Figure 4 Overlay of Origin-Destination data on the Big Data analytics platform

4. The Community of Communities Online Platform

4.1. How to build and develop online communities to support and enable holistic sustainable urban planning?

4.1.1. Background

In the last years the experts from Israel Smart Cities Institute consulted with a lot of cities and companies around the world and supported their transition to become smart cities and enable holistic sustainable urban planning.
This is a report with recommendations for all stakeholders who want to learn how to use online communities to enable holistic sustainable urban planning. All the recommendations are based on our past experience and include examples from the CoC (Community of Communities) which is our online community in TRANS-URBAN-EU-CHINA project.

4.1.2. Why online communities?

In recent years, with the development of technology, urbanization processes, and the simple transitions in the global world, competition between cities in every country and in the world as a whole has increased. The cities want to attract the best quality youth, minds, and populations to move in and raise a family in the city.
In order to stay relevant, one must be flexible and able to adjust to rapid change, and so the system must embrace new ways to communicate with its residents, move away from the traditional municipal one-to-many methods and attempt to create a platform that will support openness, equality, trade, tourism and culture. This is very much in line with the global vision of the current municipality which is expected to deliver much more than efficiency and excellence in services for residents.
The new vision prioritizes a deeper engagement with the community, involving open dialogue with and between residents, the creation of new models for trading and sharing goods and services and most importantly, making cities liveable and equitable [10], [11].

The communities that previously had formed naturally for survival, on a geographic or family basis only became a possibility for all, through technological developments.
The online communities have become part of our daily routine and are used to consult, study, and explore new topics with a variety of interest groups and people with whom we have a common ground.
These communities that are formed around different interests, common identities or needs, enable everyone to express, explore, study and evolve in the personal and professional levels, locally and globally and even across sectors and cultures.

Communities have the power to bring about positive and negative changes, so even within a community that is naturally formed or formed around a goal, we need leaders who know how to set boundaries, rules and standards.
In addition, the online communities can serve as a supportive framework for frontal activities in many cases. For example: during a lock-down as in the outbreak of the Coronavirus, the creation of communities can benefit the members a lot of in different ways. In the TRANS-URBAN-EUCHINA project, the CoC supports the ULLs' activities and enables the platform for different kinds of experiments. If we continue with the Coronavirus situation as example, we can learn from our experience with the CoC that people almost automatically look for an online community. During the crisis, the CoC enabled all the community members to share their ideas, thoughts, and tips about their situation, and to get feedback and comments from the others. We learn from the CoC experience that people are excited about the opportunity to express their knowledge online, especially when it comes

to a global community - then they get the chance to communicate, collaborate and expand their own network. There are even more benefits to online communities in different kinds of sectors:

1. In the private sector-global companies which want to connect their workers from all over the world can create a community to support each other and continue with their work even during the challenging situation.
2. In the public sector- municipalities which want to help their citizens that are in a need can use the online communities as a tool that enables accessibility and communication.
3. Existing communities can engage their members to share solutions for daily problems, enrich each other and become even more meaningful in these tough times.

Our mission in this project is to create an online 'Community of Communities' to cover the social aspect, and to serve as an online "one-time stop shop" platform for all stakeholders. This platform allows for knowledge sharing and knowledge creation across borders in online Living Labs where real estate developers, policy makers and citizens can e-meet, share insights and expectations, post and rank ideas for new joint projects and capitalize on lessons learnt from past projects.

In the challenging time of the Covid-19 the ULL activities have been paused and the CoC platform served us as online ULL. Initially, the new reality of uncertainty, concerns, and the different routines caused most members of the community not to be emotionally free to pursue online activities. After a few weeks, we felt the desire to share and discuss and began to drive the platform activity. We did seven interviews on our CoC platform with our community members and other experts like Prof. Otthein Herzog, Dr.Shaul Lev, Giorgio Prister, and others about their thoughts, challenges, solutions and recommendations, in order to provide added value, knowledge of what is happening in other countries and cities in the world, and tools to deal with the situation. One of the experts we interviewed was Danah Zohar, an American-British author and speaker on physics, philosophy, complexity and management who teaches in the Tsinghua University in Beijing. She told us about her work in China on the topic of quantum physics and expressed her passion about working in China with great minds, advanced technologies, and new exciting projects. Danah believes that the Chinese and the Israelis have very similar personalities and only cooperation between the west and the east is necessary for innovation development for the future.
The second interesting interview was with Prof. Liu Chang, where we gathered questions from the community members beforehand, and she told us her personal stories from the lock-down in China.
The last and very inspirational interview was with Liora Shechter, CIO of Tel Aviv, who reported on the DigiTel Resident's Club that is a personalized web and mobile communication platform which provides residents with individually tailored, location-specific information and services. This platform facilitates a direct and holistic connection between the city and residents that share their personal data voluntarily to receive great services and benefits in return. The ordinary benefits of the application are as mentioned in Tel Aviv municipality website[8]:

- Discounts at Tel-Aviv's numerous culture, sports, arts and recreation facilities.
- Live updates about what's happening in the city, adapted to the user personal interests: culture, music and or/ art events, health and lifestyle, sports, children's activities and much more.
- Live updates about what's going on in the vicinity of the user's address and announcements about community events and the blocking and restoration and construction of streets/ areas.

During the covid-19 crisis the municipality needed to adapt on the one hand new ways to give added value to the residents for staying relevant, and on the other hand to keep them updated and keeping the rules. Therefore, Tel Aviv used the familiar platform that all the residents already know and added more relevant information and features, e.g., in the section where residents can report on blocking scooters, they now can report about aid for elderly people. Tel Aviv also tried to embrace the innovation and startup community to help them to solve the coronavirus issues. One of the

[8] https://www.tel-aviv.gov.il/en/Live/ResidentsCard/Pages/default.aspx

applications is Tribio that was selected by the department of education in Tel Aviv: they could activate 1000 volunteers to use the application and to try to help others.
Another activity was an international virtual Hackathon that continued for 72 hours and invited solutions to support SMEs in Tel Aviv during this tough time for them. All the solutions became accessible to be used by any country that participated in the Hackathon and all the startups got the chance to make connections and get feedback from experts from all over the world. The experts from the Israeli Smart Cities Institute participated in the Hackathon jury and were mentors for startups.

Despite the many benefits of operating a community and its success, it requires a lot of focus, creativity and soft skills - especially when it comes to a new community that you want to establish.

4.2. Recommendations for establishing a successful new community in a city:

- The members-when it comes to the local authority the target audiences are diverse so it is worthwhile to create one large community that will also contain special interest groups much like the CoC. The CoC include students, experts, decision makers, professors, etc. The digital encounter between all different audiences brings a unique connection and discourse that isn't necessarily possible in other conditions. When it comes to cities, making connections between different audiences can create a sense of belonging. For example, SIGs can be developed according to neighborhoods and streets or on the basis of business owners, families with children, or young couples.
- The platform- after selecting the target audience and the initial topics of interest for ideal community members, you need to think carefully about what is the right platform to use for your community.
  We have learnt, there is no single and definitive answer to the question:
  What is the best way to choose a platform for my community?
  Therefore, we recommend four tips to help you stabilize your community on a central platform
  A. Make a small pilot while engaging potential end-users in the process- start with one small pilot on the chosen platform and ask potential users to assist you and give feedback afterward. In this way, you can draw preliminary conclusions and learn how and which improvements you should do, you also can consult about the community name, common goals, and who will be the other potential stakeholders.
  B. To use existing platforms that are already in use in the community of interest- As an example of this case, we learnt the WeChat platform is used in China but not in Europe. When we started our work in China, we all adapted ourselves to the ways of communicating and acting there to reach the relevant users.
  C. Combine multiple platforms together for maximum coverage- further to the previous section throughout the project, we continued to use WeChat to post events, contact community members, and reach to new potential members in parallel to the maintenance of the chosen platform.
  Maintaining relationships across multiple platforms may take a lot of resources and time but is necessary. You should think of it like running a personal Facebook account while also use your personal Linkedin- the publications reach different target audiences and the content is tailored to the relevant platform.
  D. Allow improvements and flexibility for changes-the beginning is always more difficult, so you need to be open-minded and flexible to change the initial plan and adjust yourself to the emerging reality.
  For example: When we launched the platform we wanted to conduct all the interviews and workshops there, but it turned out that there are other and more convenient platforms to do so, we were flexible to conduct the activities on other platforms and then upload the content to CoC.

- Network traffic- we all know that even if we did extensive planning and lots of preliminary tests, sometimes the reality is not as we imagined. The best solutions we can offer are persistence and teamwork!

In addition, when it comes to creating a new community in the city, the marketing resources of the city can be routed to invite residents to join the community.
The most important thing when doing this is to make sure that the benefits are shared by both the residents and the decision makers in the city. A good example of this is the process Tel Aviv municipality pursues with the DigiTel smart application for online public participation that brings value to both the residents and the municipality (a win-win smart solution). The residents share their personal data voluntarily to get great services and benefits to use in the city in return.

5. Interrelationships between Air Pollution and Transport

5.1. The interrelationship between air quality and transportation

The impact of outdoor air pollution on the burden of disease in the world's cities is huge [10], [11], [12], but the formation of air pollution is complex and has yet to be fully understood [13], [14]. Motor vehicle traffic emissions contribute a significant proportion of pollutants in cities globally, particularly in some developing countries. In China, the situation is serious as well, especially the high PM2.5 and PM10 concentrations in the ambient air of a number of regions, [2],[14]. The linkage between air quality and transportation has been evidenced by certain previous studies. Hu et. al. [15] proposed an index called Mutual Information of Air Quality-Traffic-Meteorology to describe the combined effects of meteorology and traffic restrictions. Karner et. al. [1] found that different pollutant concentrations had significant different near-roadway dispersion mechanisms. Wang et al [16] proposed the mechanism of air pollution terrain nexus. Research has suggested the complexity of air pollution and the multiple influential factors in cities [17]. Studies disclosed that the concentration of PM2.5 had a strong spatial correlation with SO2 emission, inversion temperature, GDP, and population density [18]. Emission control has reduced the concentrated level of PM to some extent lately, unfortunately unfavorable weather and climate partially counteract the emission control effects [19], [20], [21].

5.2. Basic information of the four Urban Living Labs

This section contains some fundamental data on four ULLs in China under considerations.

Tianjin is located in northern China and is the largest port city in northern China. The city has 16 districts with a total area of 11966.45 km^2. At the end of 2019, the permanent population was 15.6183 million, the urban population was 13.0382 million, the urbanization rate was 83.48%, and the permanent population was 9.8 million (2009).

Wuhan, the capital of Hubei Province, is located in the east of the Jianghan Plain and in the middle reaches of the Yangtze River. As of the end of 2019, the city has 13 districts under its jurisdiction, with a total area of 8569.15 km^2, a built-up area of 812.39 km^2, a resident population of 11.212 million, and a regional GDP of 1.62 trillion.

Baoding, located in the heart of Hebei Province, is the central city of the Beijing-Tianjin-Hebei region and part of China (Hebei) Free Trade Pilot Zone. As of the end of 2019, Baoding City has a total area of 22,190 km^2 and it has a national high-tech zone with a total permanent population of 11.86 million and a gross product value of 377.2 billion yuan.

Jingdezhen, alias "Porcelain Capital, is located in the northeast of Jiangxi Province. Jingdezhen is the world's porcelain capital, the cradle of China's helicopter industry. In 2019, Jingdezhen covers a total area of 5,256 km^2, achieving a total regional production value of 92.611 billion yuan and has 2 districts, 1 county-level city, 1 county.

5.3. Data and Analysis Methods

5.3.1. Data collected for the analysis

Both monthly and real-time air quality data, concentrations of gaseous pollutants and fine particle (AQI, NO_2, O_3, SO_2, CO, $PM_{2.5}$, PM_{10}), are derived from the Platform for AQ Intelligent Management[9]. The monthly air quality data for the four ULLs ranges from December 2013 to April 2020. Real-time air quality data are collected three times per day.

The annual transportation data ranging from 2013 to 2019 are collected from the National and Local Statistical Yearbooks.

We retrieved the locations of industrial PoIs of construction, machinery and electronics, chemical and metallurgy, mining, and factories in four ULLs From AMap[10].

Real-time traffic data of Tianjin and Wuhan are also obtained from AMap for the same period as the real-time air quality data. As there is no corresponding data available for Baoding and Jingdezhen, we will apply some substitutions that will be discussed later.

5.3.2. Analysis methods

The analysis methods used include Big Data Analytics for non-conventional data and concentrate on

- Visualization of some data to determine the variations of real-world data over time,
- Correlation analysis to determine the interdependencies between data,
- Non-parametric tests to determine similarity and class membership of city-specific environmental data.

In addition, Neural Network Technologies were used in order to develop a BPNN model for the Air Quality Index (AQI) prediction in cities. It delivers satisfactory AQI predictions based on a data set of road properties, traffic, and weather data.

[9] PALM at www.zq12369.com
[10] m.amap.com

6. Air quality and transport in four Urban Living Labs

6.1. Monthly AQI data

The pollutants participating in the evaluation of AQI grading calculation are SO2, NO2, PM10, PM2.5, O3, CO and additional six items. We selected the AQI data from 2014 to 2019 to study the air quality of the ULLs Tianjin, Baoding, Wuhan and Jingdezhen and the data granularity is one value for a month.

The chart below shows the monthly average AQI of the four cities from 2013-12 to 2019-02 (Jingdezhen: 2014-12 to 2019-02), please note that the higher AQI, the worse the air quality.

According to the data, the air qualities of the four cities can be ranked from the worst to the best: Baoding, Tianjin, Wuhan, Jingdezhen.

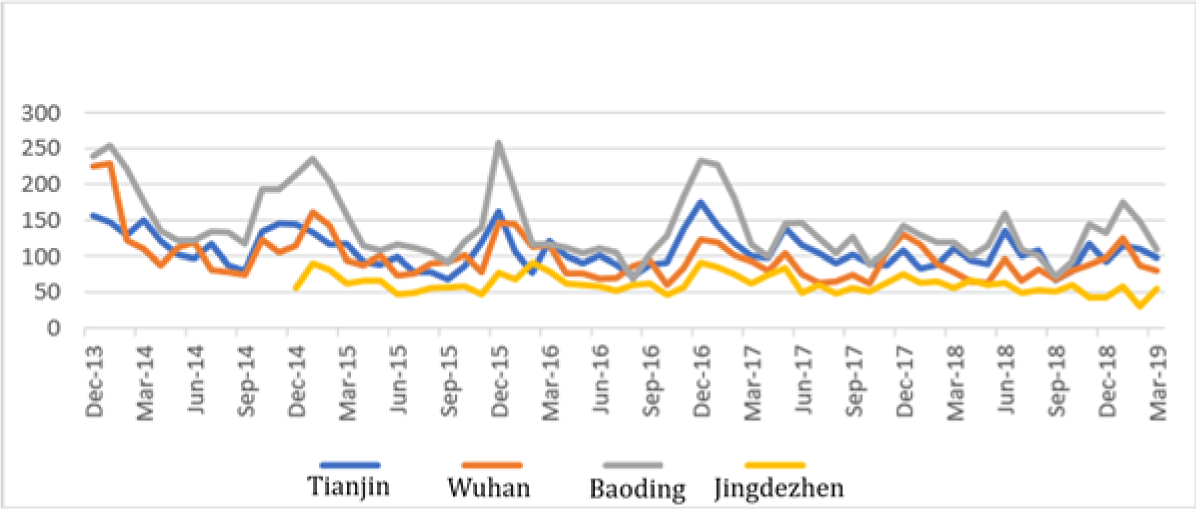

Figure 5 Average of monthly AQI for four ULLs

The peak AQI of four ULLs shows a decreasing trend after 2016. According to the diagram, the annual AQI change of cities is U-shaped: higher in winter and autumn while lower in spring and summer. That is, July-October each year is the months with the lowest AQI index in a city. And starting from November, the AQI index begins to show an upward trend, and it peaks between December and February of the coming year, and gradually declines in March.

Six urban pollutant indicators for the assessment criteria constituting AQI, we found that the concentration of CO in pollutants is the lowest, the concentration of PM10 is the highest, and the concentration of O3 in May to October is significantly higher than other months, and other concentrations of pollutants are exactly the opposite to O3, which are lower in May-October, but significantly higher in other months. The changing pattern is very similar to the one of monthly average of AQI.

According to the total of various indicators in each year from 2014 to 2018, we found that the concentrations of various pollutants PM2.5, PM10, SO2, CO, NO2 showed an annual decreasing trend and the O3 concentration in Baoding and Tianjin increased year by year. The concentration of O3 in Jingdezhen and Wuhan tended to be stable. All in all, urban smog pollution in these cities has being reduced, and it is gradually developing towards a favourable situation.

6.2. Annual traffic data

Traffic data mainly includes data on population, public transportation, and urban roads. The data of Tianjin and Wuhan are more complete, while some data from Baoding and Jingdezhen are difficult to obtain if not impossible.

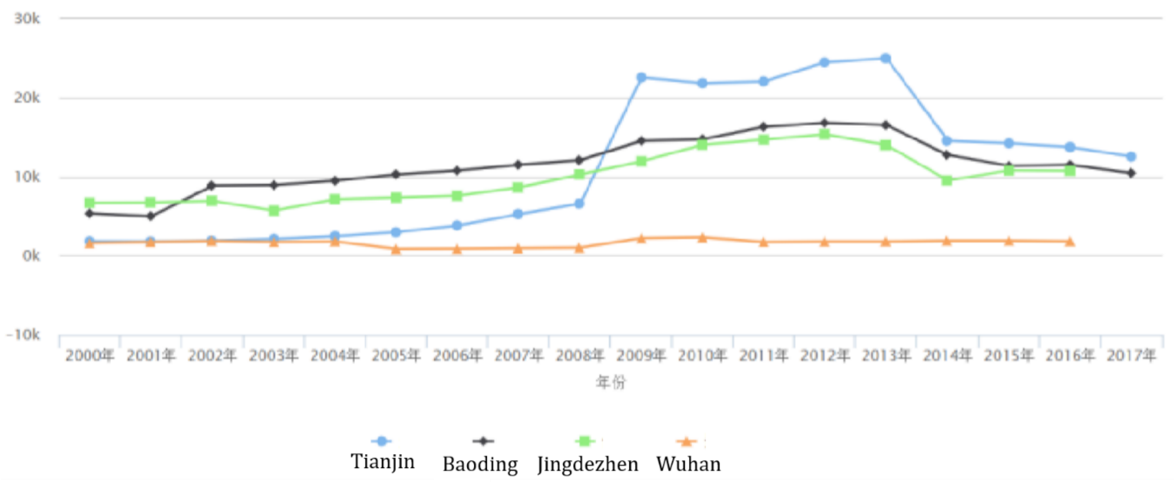

Figure 6 Average Highway passenger traffic of four ULLS

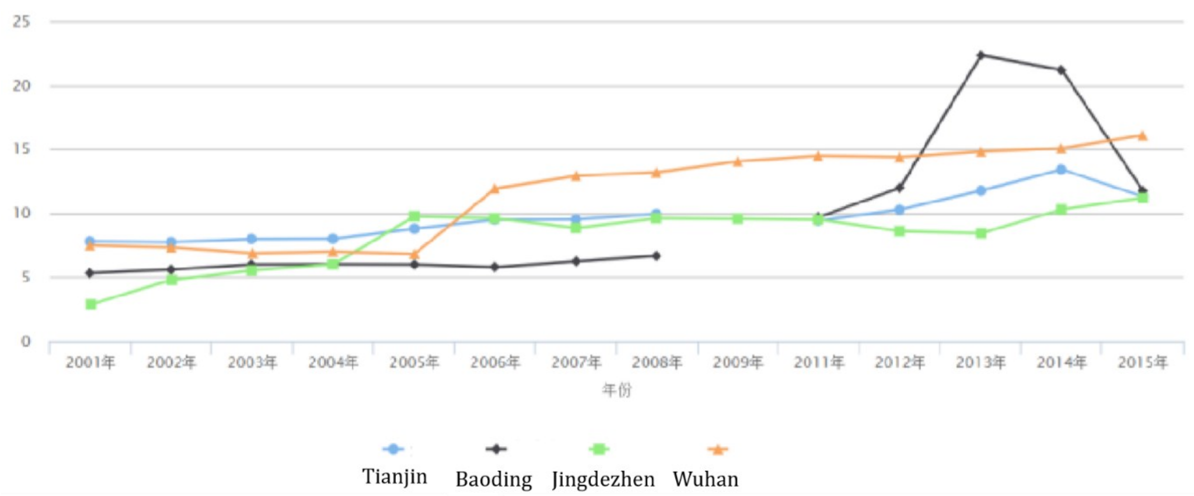

Figure 7 Average number of buses per 10,000 people for four ULLs

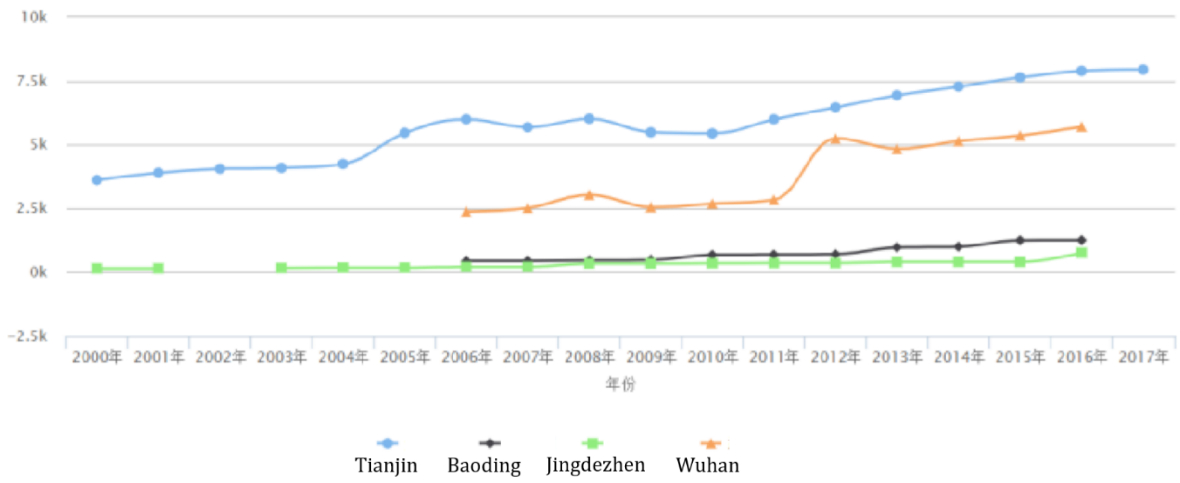

Figure 8 Average urban road length for four ULLs

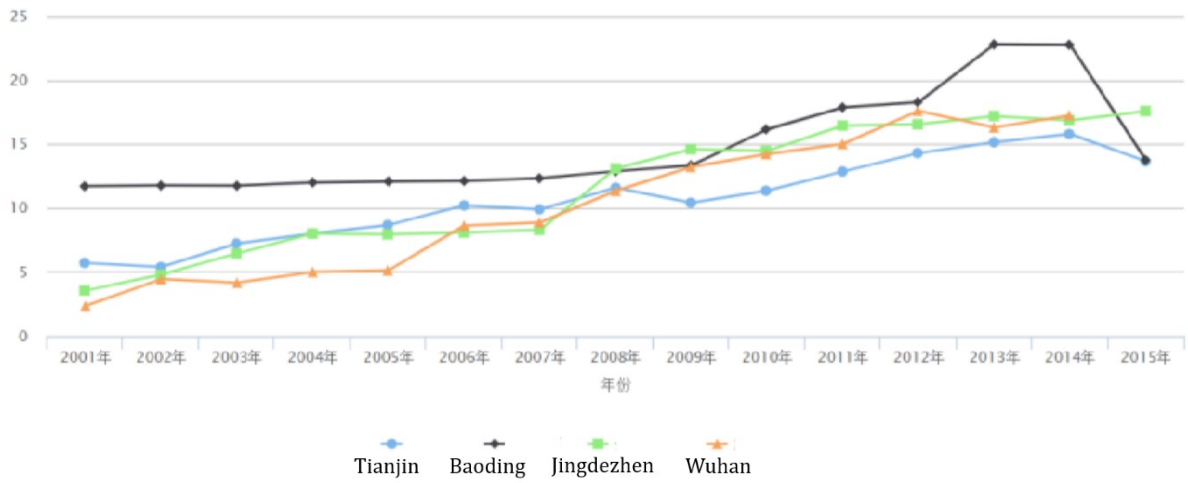

Figure 9 Area of paved roads per capita for four ULLs

In terms of the total urban volume, Tianjin, Baoding and Wuhan have an advantage in passenger traffic on highways, and the lengths of urban roads from high to low are Tianjin, Wuhan, Baoding and Jingdezhen. The number of buses per 10,000 people in Jingdezhen is higher than that of the other three cities, and so is the per capita paved road area, which reflects the per capita carrying capacity of urban traffic.

6.3. Point of Interest data for four ULLs

The distribution maps of industry location PoIs in four ULLs is shown below. We can find that the distribution of the big urban industries is related to the distribution of urban traffic and roads. This correlation is particularly significant in Baoding.

Figure 10 Industry PoI data for Tianjin

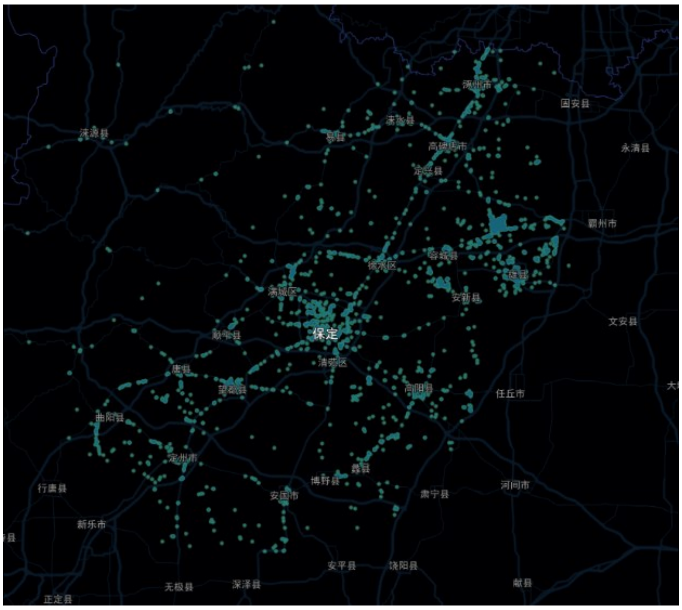

Figure 11 Industry PoI data for Baoding

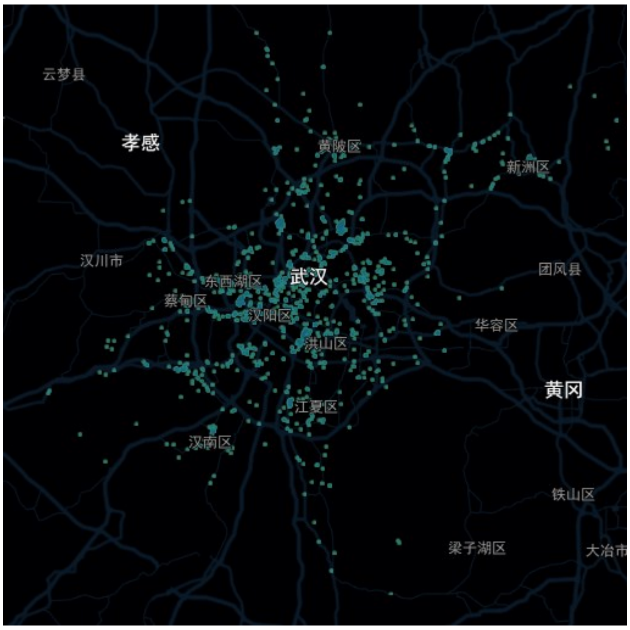

Figure 12 Industry PoI data for Wuhan

Figure 13 Industry PoI data for Jingdezhen

By collecting and analysing PoI data on industries and factories, we found that the location pattern of the mining industry somehow overlaps with the one of air quality, especially for Baoding and Jingdezhen. A semantic analysis of the PoI names of the factories reveals that the industrial sectors of the four cities are different. The key word for Baoding is plastic, that is, the primary processing of minerals; the key word for Jingdezhen is ceramics and craft products; Tianjin is dominated by mechanical processing and Wuhan by textile, printing, and furniture industries. It is conceivable that the industrial sectors of a city plays a role influencing the air quality of that city. This observation motivates us to include these datasets in the analyses described in the following sections.

7. Correlation analysis

7.1. Real-time datasets

Many cities in China are expanding their public transportation construction projects aiming at proving a better transportation infrastructure and more convenient access to the transportation networks. To reveal the relationship between air quality and transportation construction, we did a correlation analysis which is a method of statistical evaluation used to study the strength of a relationship between two, numerically measured, continuous variables. This particular type of analysis is useful when the goal is to establish possible connections between variables. However, other variables that are not present in the research may also have impacted the results. If a correlation is found between two variables it means that a systematic change in one variable implies that there is also a systematic change in the other one; the variables are changing together over a certain period of time.

The section also demonstrates the application of various methods/models to conduct the correlation analyses.

7.2. Correlation analysis results

Overall, Jingdezhen is quite different from other three cities. The air quality of Baoding, Tianjin and Wuhan is negatively correlated by year, indicating that the air quality of these three cities has a decreasing trend every year, while the air quality of Jingdezhen has little correlation by year. The air qualities of Baoding, Tianjin, Wuhan and public transport construction have a clear negative correlation trend, that is, there is a correlation between more roads and public transportation and a betterair quality. At the same time, also the structural change of the industry could have contributed. Nevertheless, the air quality of Jingdezhen and public transportation construction have a positive correlation trend, that is, the more roads and public transportation projects, the worse the air quality. In addition, it was also found that the public transport construction in Baoding, Tianjin and Wuhan had the most obvious impact on SO2 and the weakest impact on NO2 while for Jingdezhen this turns out just opposite. Its public transportation construction has the most obvious impact on NO2 and the weakest impact on SO2.

The following diagram illustrates the sample of correlation matrix to be used in the analyses between air quality features and traffic data features. The air quality features include AQI, SO2, NO2, PM2.5, PM10, NO, and O3, while traffic data features include actual numbers of taxis and bus, the per capita road area of the city, the total population, the length of urban roads and the area of mechanized cleaning and cleaning of urban roads.

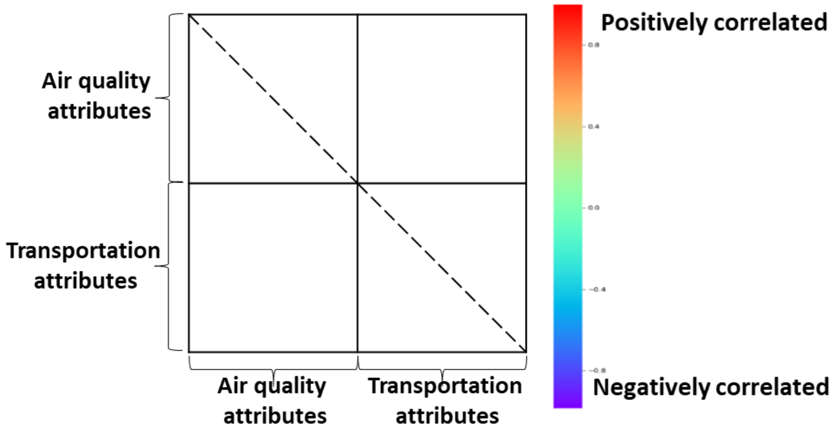

Figure 14 Schematics of the correlation matrix used in the subsequent figures

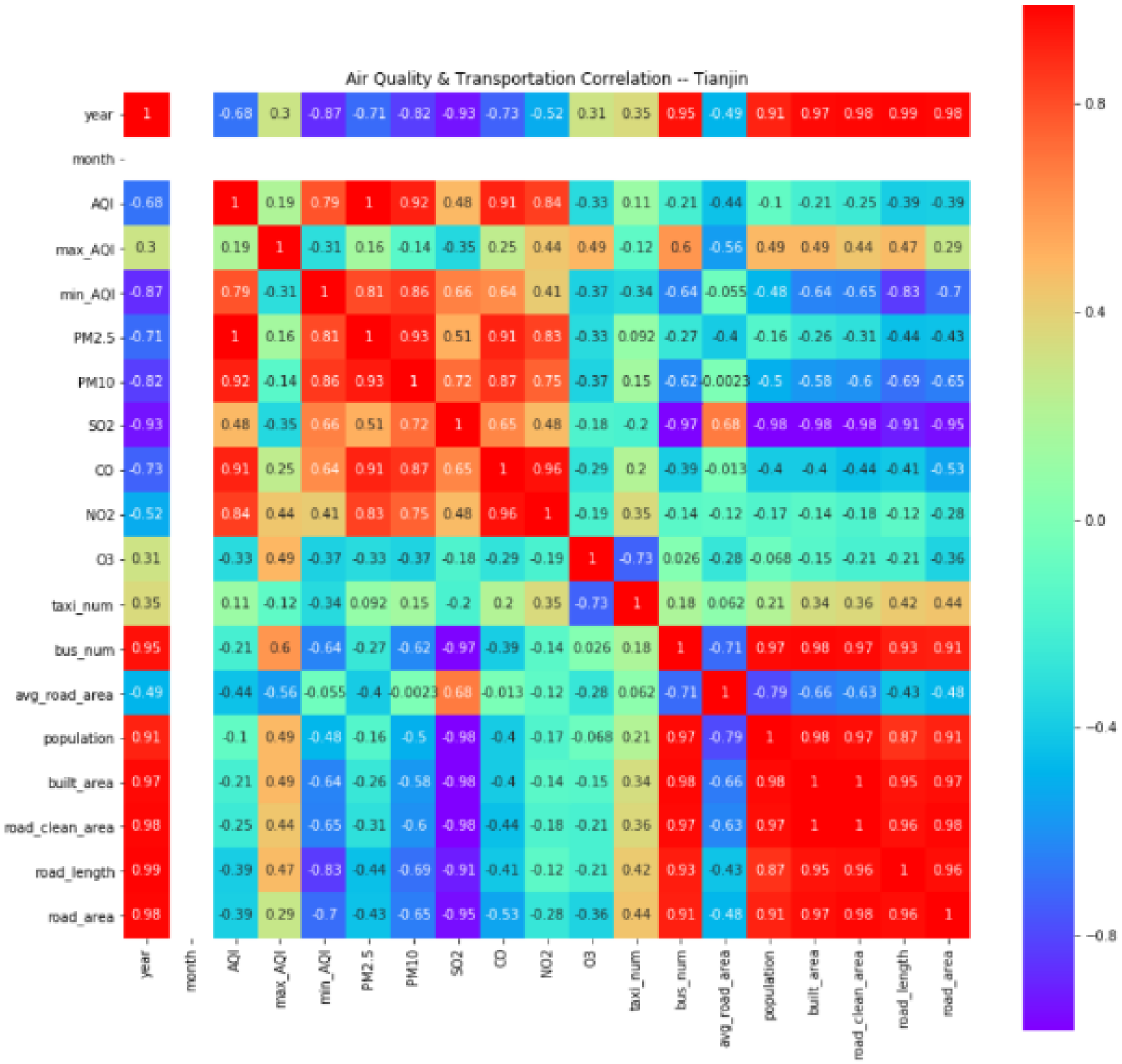

Figure 15 Correlation matrix of Tianjin

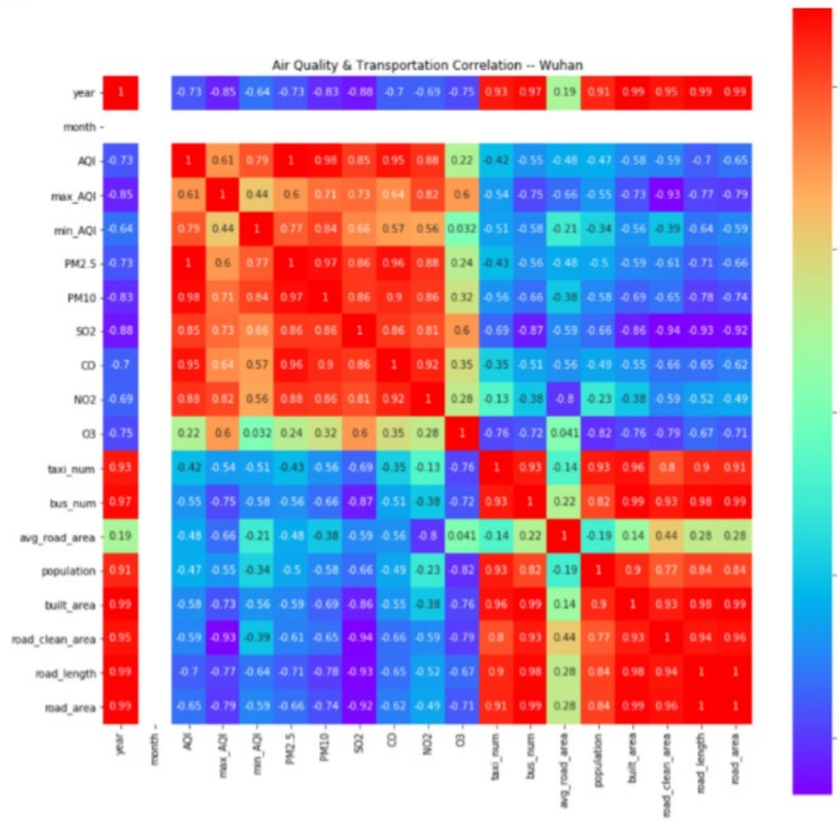

Figure 16 Correlation matrix of Wuhan

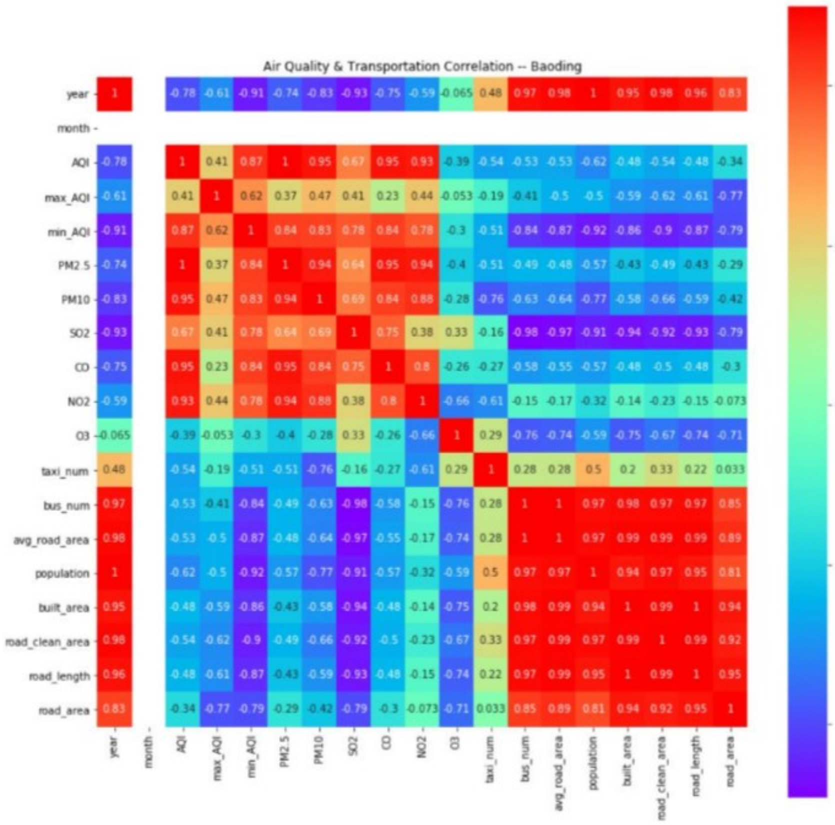

Figure 17 Correlation matrix of Baoding

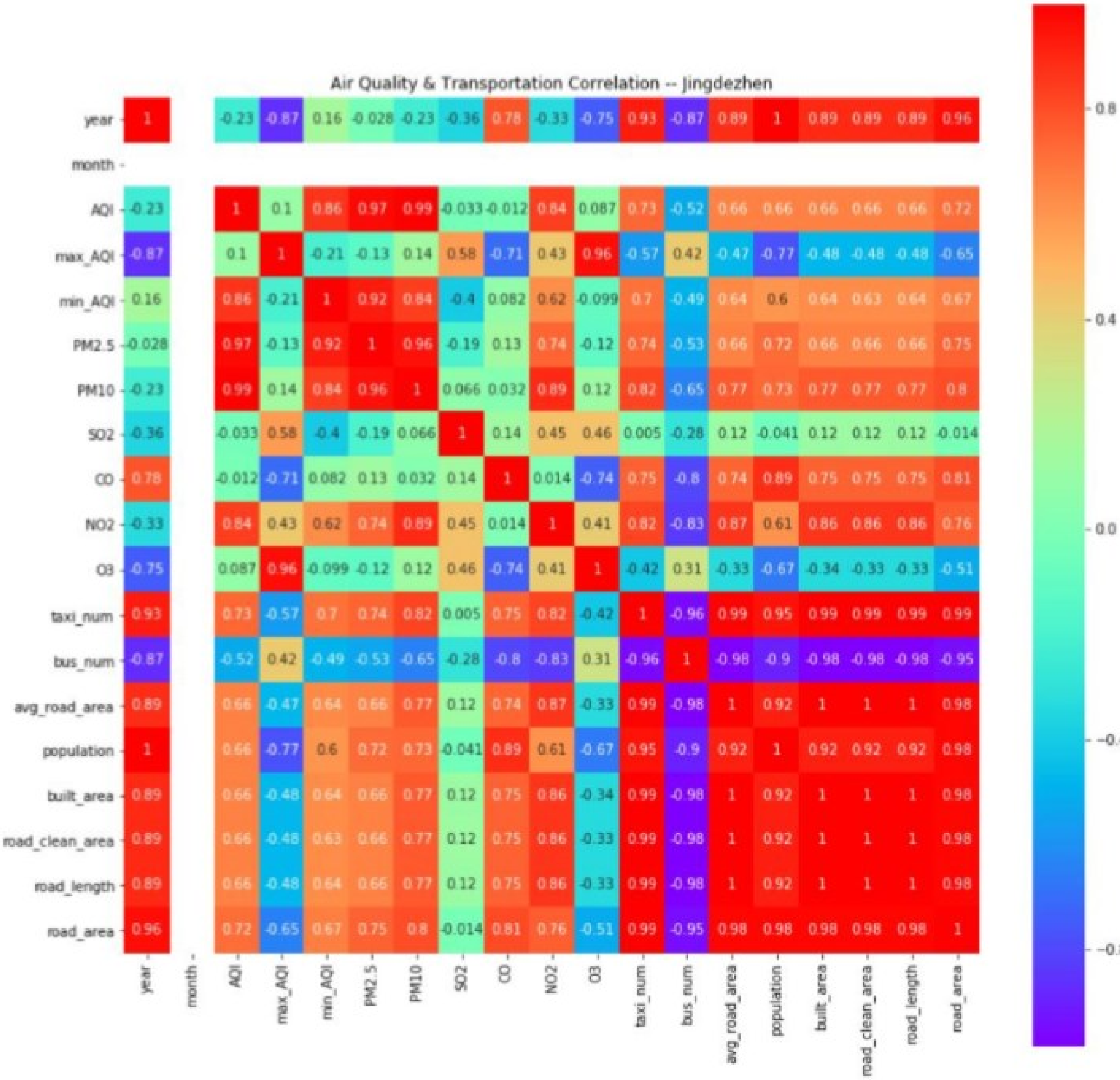

Figure 18 Correlation matrix of Jingdezhen

In the correlation matrix diagrams of Tianjin, Baoding, and Wuhan, the three cities show a clear and identical color patch distribution trend, which implies a similar correlation relationship. The number of urban buses, the per capita road area, the road clean area, and the road length are negatively correlated with air quality.

But for Jingdezhen, it can be found from the color block distribution of the correlation matrix that the growth of urban traffic may have a negative impact on air quality, as the AQI increases with the growth of the public transportation index. The reasons for this – unexpected -positive correlation must be researched in more depth.

Overall, Jingdezhen is quite different from the other three cities. The air quality of Baoding, Tianjin and Wuhan is negatively correlated by year, indicating that the air quality of these three cities has a decreasing trend every year, while the air quality of Jingdezhen has little correlation by year. The air quality of Baoding, Tianjin, Wuhan and public transport construction have a clear negative correlation trend, that is, the more roads and public transportation, the better the air quality. Nevertheless, the air quality of Jingdezhen and public transportation construction have a positive correlation trend, that is, the more roads and public transportation projects, the worse the air quality.

In addition, it was also found that the public transport construction in Baoding, Tianjin and Wuhan had the most obvious impact on SO2 and the weakest impact on NO2 while Jingdezhen shows just the opposite. Its public transportation construction has the most obvious impact on NO2 and the weakest impact on SO2.

7.3. Non-parametric tests

The number of taxis in Jingdezhen and Baoding is proportional to the AQI, while the number of taxis in Wuhan and Tianjin is inversely proportional to the AQI. Therefore, it is suspected that the relationship between traffic and air quality in cities of different sizes could be different.

In order to study the similarity of the four city models, we use another statistical analysis method to infer the overall distribution shape. The Kruskal-Wallis H test[11] was employed to perform non-parametric tests on the public transport construction indicators of the four cities from 2013 to 2017.

	Tianjin	Baoding	Wuhan	Jingdezhen
Tianjin	\	0.3379	0.8480	0.5653
Baoding	0.3379	\	0.27744	0.9491
Wuhan	0.8480	0.27744	\	0.6547
Jingdezhen	0.5653	0.9491	0.6547	\

Figure 19 Non-parametric test of 4 ULLs' public transport construction indicators 2013-2017

The result of this non-parametric tests is represented as an index: the higher the index, the higher the similarity between two cities. The results show that from the perspective of the five-year growth rate of each indicator, Baoding is similar to Jingdezhen, while Wuhan is similar to Tianjin.

The result validates our hypothesis indicating that we are able to analyse a group of cities with similar characteristics, i.e., with the same distribution of the values of public transport construction indicators, instead of individual cities. This result enables improved analytical efficiency, as cities can be classified according to the public transport construction indicators, and only a representative of each class can be analysed in-depth..

[11]From https://en.wikipedia.org/wiki/Kruskal%E2%80%93Wallis_one-way_analysis_of_variance
"The **Kruskal–Wallis test** by ranks, **Kruskal–Wallis *H* test**[1] […] is a non-parametric method for testing whether samples originate from the same distribution.[2][3][4] It is used for comparing two or more independent samples of equal or different sample sizes."

8. A Real-time AQI prediction model

Some research indicates that the AQI could be influenced by the traffic condition near the monitoring station and the industrial entities in the neighbourhoods. Motor vehicles are known for their emission of CO, NOx and particulate matter, while industrial entities are known as the main source of pollution in built environments. To find the deep relationship between air quality and transportation construction, we use the real-time data to build a model disclosing how traffic and industrial entities impact the AQI and predicting the AQI, e.g., in respect to future developments.

The technology of Back Propagation Neural Networks (BPNN) was used to generate the prediction model and to perform the forecasting tasks.

8.1. Neural Networks Overview

An Artificial Neural Network obtains the weights and structure of its network through supervised learning in training phase, where it exhibits a strong self-learning ability and adaptability to the environment. The learning process of a neural network is based on sub-symbolic logic where it adapts its weights based on the data provided. Thereby, the internal relationship between input and output is determined so as to find a solution to the classification problem. The training samples, and not the Neural Network itself are based on empirical knowledge and, maybe, rules of the problem space.

Taking the picture below as an example of a simple Neural Network, each circle represents a neuron, *i* represents the input layer, *h* represents the hidden layer, *o* represents the output layer, w represents the weights between neurons, and b represents the offset, which is used to perform the weight calculation after the Neural Network training phase.

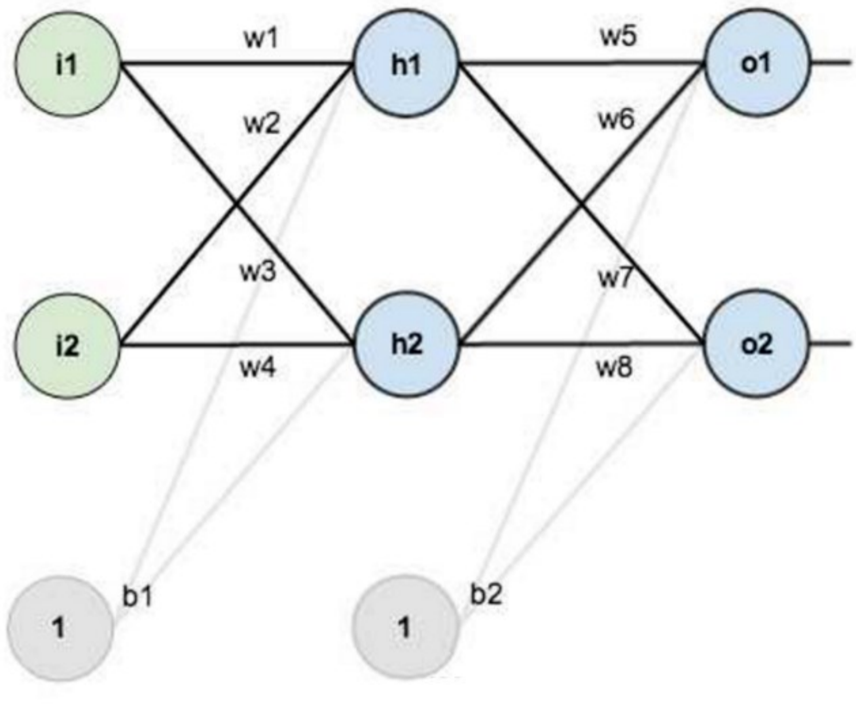

Figure 20 Example Neural Network

8.2. Advantages and Realization of a BPNN

The main advantages of the BPNN technology are:

1. Non-linear mapping ability: they are able to solve non-linear problems.
2. Self-learning and self-adaptivity: they constantly adjust the weights during operation.
3. Fault tolerance: Partial errors are tolerated in the training samples, which does not affect the results.

The implementation of a BPNN-based prediction model can be split into the following steps:

1. Data extraction normalization.
2. Train the BPNN using the training set and record the final network weights.
3. Test the BPNN using the test set input and check the results.
4. Use the trained network to predict the output under the specific input conditions.

8.3. Data preparations

The following figure shows the feature vectors used for Neural Network model input. They can be divided into three types: traffic data, weather data, and air quality data. Unblocked ratio, congestion ratio, slowing down ratio and traffic condition are traffic data; the first three are in the form of percentages, and the last one is expressed by the average speed measured on the road. Temperature, relative humidity, cloudiness and wind speed are weather data that have a big influence on the spread of pollutants. The remaining features are air quality data, which are used to predict the AQI at the next period.

Unblocked ratio	Traffic condition	Congestion ratio	Slowing down ratio	Visibility	Temperature	Relative humidity
85.19%	2	3.70%	11.11%	15.8	35	0.42

Cloudiness	Wind speed	NO2	CO	O3	SO2	PM2.5	PM10
0	5.4	25	1	265	62	62	82

Figure 21 Input feature data

8.4. Prediction results

Before starting the prepared training set transformed into the data matrix, the input data matrix and the target data matrix of the training set need to be normalized, because there are large value differences in each data matrix dimension.

When training the model with the training dataset, the weights and thresholds are adjusted once for each element of the training set. The maximum training number of the parameters (epochs) was set to 50,000, the network learning efficiency to 0.01, and the magnitude of the target error to be achieved by the trained network to be 10^{-3}.

During the backpropagation process, the standard momentum gradient descent algorithm is used, and the momentum factor is set to 0.9. The training of the Neural Network was completed once the Neural Network target error did not change for six consecutive iterations (epochs). In this experiment, since there is no problem related to slow backpropagation convergence, the common applied Mean Square Error (MSE) is selected as the loss function. We choose half of the MSE for optimization reasons.

We conducted a series of computational experiments, through which the parameters and configuration of the underlying Neural Network were determined. Applying the test set showed that the corresponding parameter setting delivered quite satisfactory training results as well as solid robustness during testing. The results described below were obtained using the model with the best parameter (configuration) settings. The corresponding results for four ULLs are presented in the following sections.

8.4.1. AQI BPNN training results

We selected the hourly real-time data of four ULLs for a period of time for training and learning. The final comparison between the training values and the real-time values is shown in the figure below.

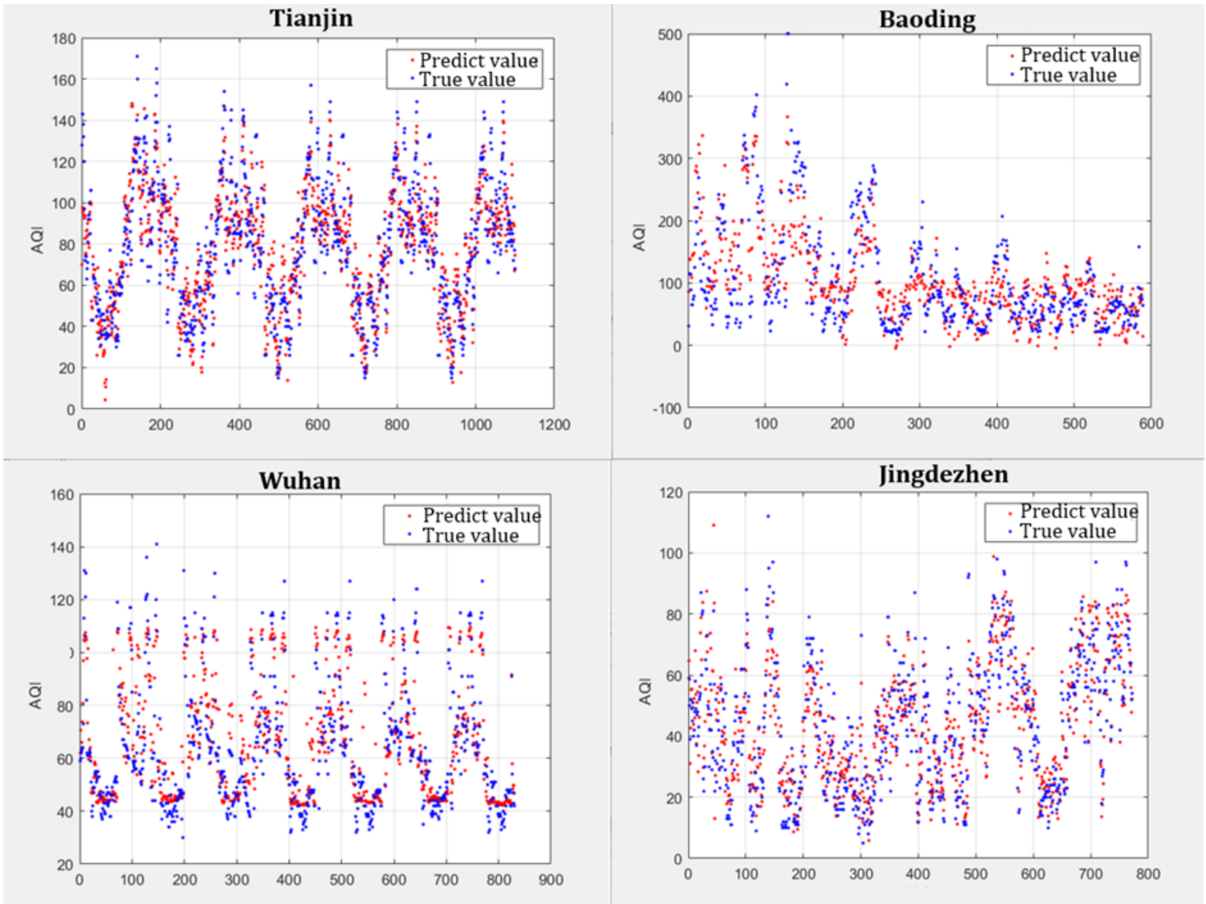

Figure 22 Comparison of AQI BPNN training results vs. real-time data for four ULLs

In the figures, the blue dots represent the predicted value after learning, while the red dots represent the real-time value. It can be seen that the training results can very well describe the trend of the air quality. The accuracy of the training results was evaluated by the MSE iteration curve and the regression fitting index.

8.4.2. AQI BPNN test results

In order to verify the accuracy of the trained model, we selected a part of the obtained data and tested the predicted AQI value. It should be noted that in order to display the test results more comprehensively, the Tianjin data was selected for a continuous period of time, while data of the other three cities were randomly selected. The comparisons between the test values and the real-time values are depicted below.

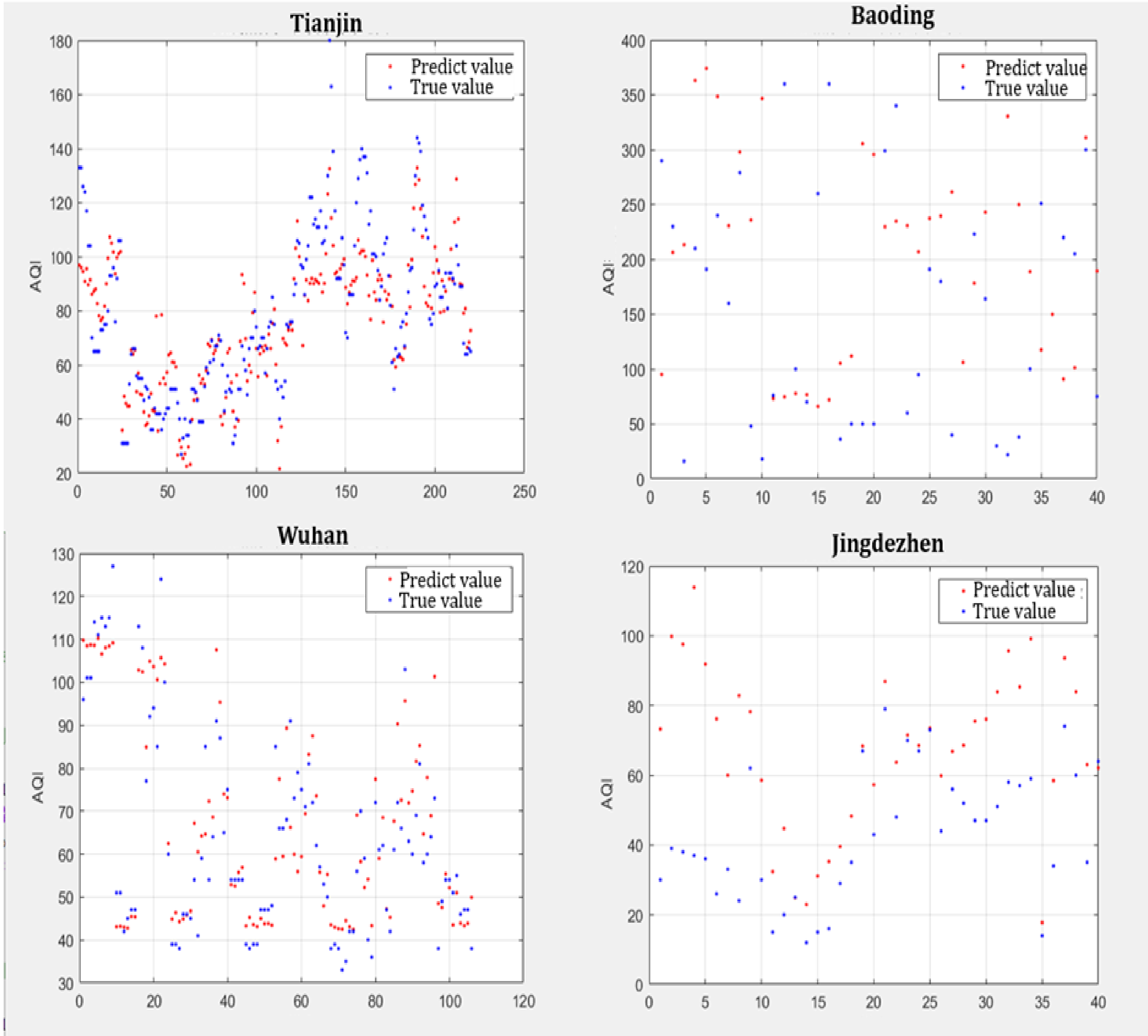

Figure 23 Comparison of AQI BPNN test results vs. real-time data for four ULLs

According to the these results, it can be seen that except for some outliers of the selected special points and with the exception for Baoding, the error between the predicted (tested) values and the real-world ones of most samples are within an acceptable range, independent of continuous time periods or random ones.

8.4.3. Mean Square Error after 1000 training epochs

The Mean Square Error (MSE) refers to the expected value of the square of the difference between the parameter estimate and the true value of the parameter. The MSE describes the degree of data change. The smaller the value of MSE, the better the accuracy of the prediction model in describing experimental data.

In order to evaluate the performance of the prediction model for four ULLs, we recorded the MSE changes during the training process. The MSE of the model for each ULL was recorded every 10 steps. The following figures illustrate the MSE results.

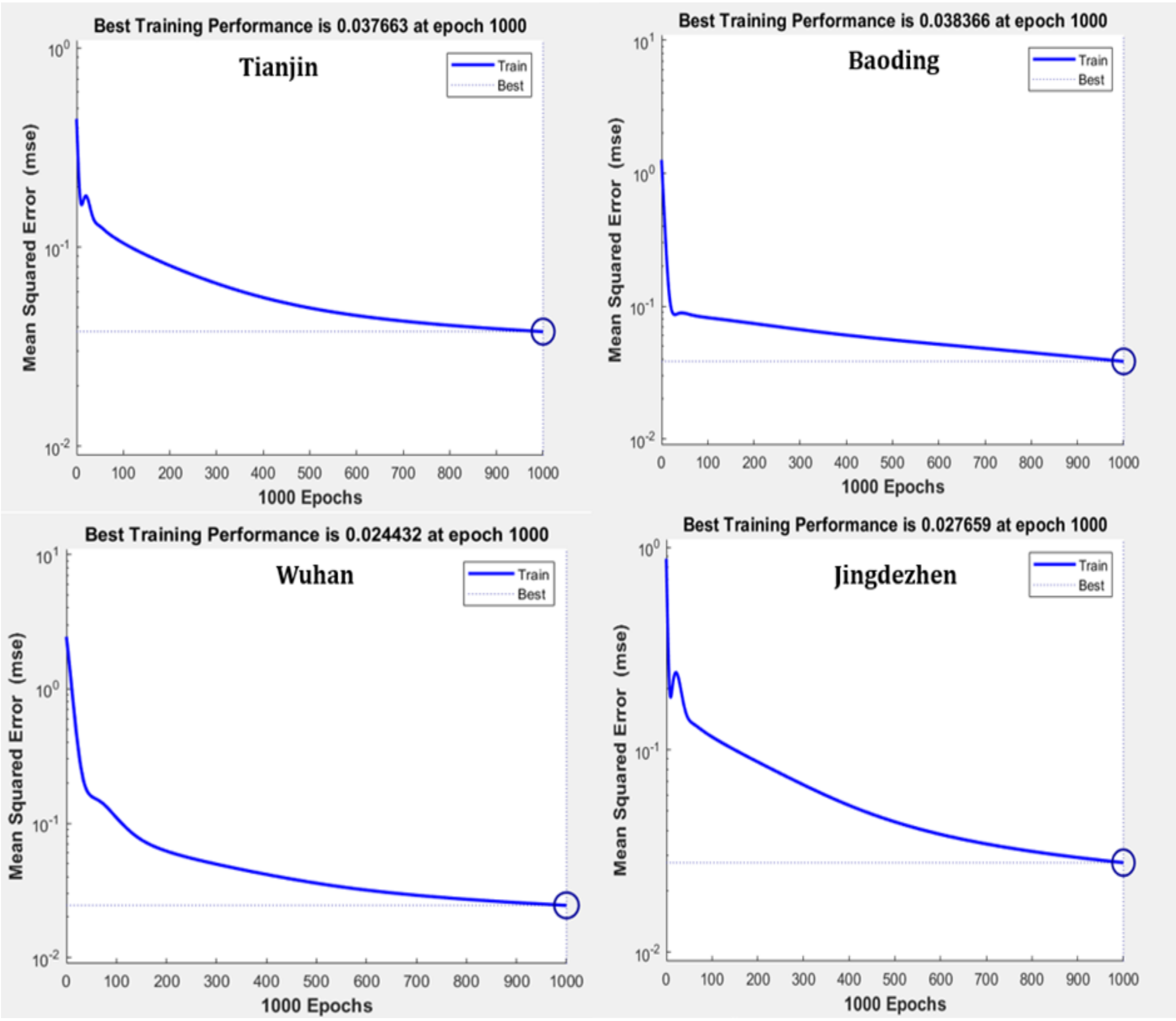

Figure 24 Mean Square Error of the AQI prediction vs. the real-time data (1000 training epochs)

As it can be seen in the above figures, the MSE decreases as the solution proceeds, and the loss function reaches its lowest value at the 1000th epoch. This result indicates that the prediction model will have even a better accuracy if more epochs are implemented.

8.4.4. Regression adaptation results

To describe the regression results from the neural network, the following diagrams show the regression fitting curve. The R value in the figure is the fitting degree, and the interval is 0 - 1. The higher the R value is, the better the model fits.

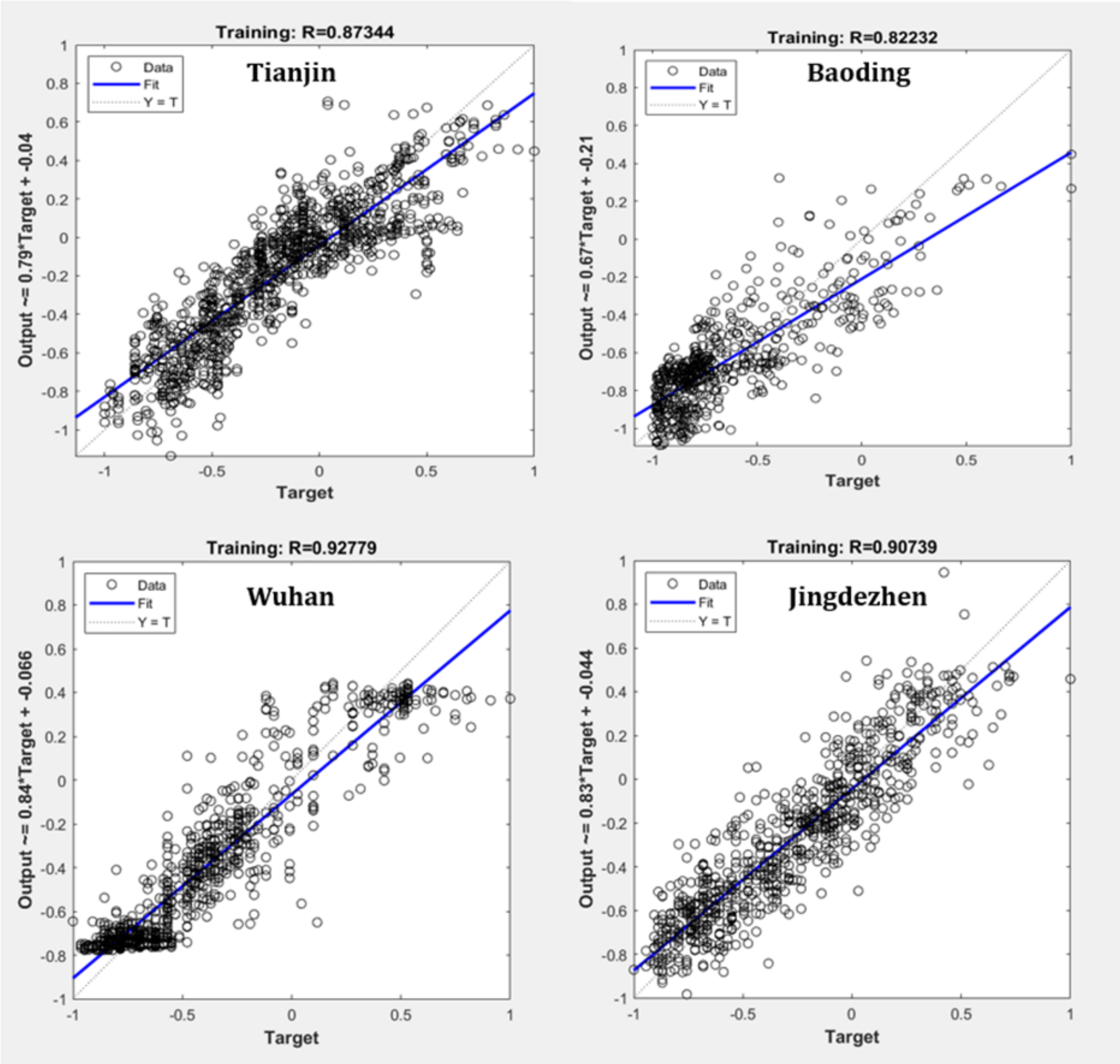

Figure 25 Regression results fitting for four ULLs

According to the experimental results shown above, where we applied the same model for AQI predictions based on the time series for four ULLs, it is obvious that the distribution of Baoding's prediction results is the most diffuse one (as mentioned earlier), and it indicates that the causes of the air pollution in Baoding are more complicated than the ones of the other three cities. The main reason could be that Baoding's urban energy consumption relies heavily on coal, and the industrial pollution caused by coal combustion has a big negative impact on the air quality.

9. Conclusions

Air quality is an important aspect of a socially inclusive city as it greatly influences the quality of life in a city by the distance of living quarters to busy roads and/or industry conglomerates. In this report, we explored the interrelationship of air quality, industrial entities, and transportation with annual, monthly and real-time data. It could be determined that the urban air quality is correlated with urban size, population, industrial infrastructures, shopping malls, and transportation facilities. The Big Data Analytics methods for descriptive, diagnostic, and predictive data together with the CoC contribution data provide an array of differentiated transformative knowledge to support urban governance and planning.

According to the correlation analysis results, it could be determined that there are different main factors affecting air quality in cities: cities with a high percentage of heavy industries, particularly those with mining industries, suffer from heavy air pollution.

By using real-time data sets to detect the correlation between air quality and transportation development or construction projects, we concluded that the time series data on road speed correlate with those of PM2.5, AQI and NO2 pollutants, independent of the impact of industrial entities on air quality during one day revealing big fluctuations.

In order to support urban planning for a better air quality, we built a BPNN prediction model, which delivers satisfactory AQI prediction results based on a data set of road properties, traffic, and weather data.. Even though the data of four ULLs with different characteristics were obtained from various public resources, the prediction results using the same method demonstrate the generalization capability of the proposed model and its applicability to other comparable cities.

In addition to this computational approach, we presented the benefits of communities and especially online communities to support the city stakeholders and to support them to make a city smarter by engaging them.

We shared our experience with online communities and used some practical examples from the CoC (Community of Communities) online platform to illustrate and demonstrate how communities can serve decision makers and how to use them wisely to create a win-win situation.

Our original plan for the CoC community was to have special events and bring people together to create the initial awareness that helps break the boundaries of hierarchy, suspicion and embarrassment. We managed to hold a few events in the ULLs before the Covid-19 pandemic, but the ULLs were closed down and all the travel to China was suspended. This challenging situation lead us to our main conclusion that in order to build and motivate the activities of a new international community and in addition, to attract key stakeholders and key factors, frontal activities must be integrated and lead the online activities. Instead, we had to take some "virtual" actions only with key stakeholders in order to replace the suddenly infeasible plan.

The main conclusion from this bottom-up approach is the importance of collaborations to achieve real success, namely the collaboration between decision makers and residents, between experts and stakeholders, and the recognition of the interrelationships in a community to drive change and generate innovation together. This approach is complemented and supported by the evidence-based analysis of real-world data and by appropriate computational models for the prediction of the corresponding city properties according to (future) planning decisions.

Thus the combination of data-based computational and transformative knowledge and human interaction models represents the ultimate combination for holistic and sustainable urban planning, as pursued and demonstrated in this TRANS URBAN EU-China project.

The insights gained through the data analyses and the online CoC platform provide a solid base for the collection of transformative knowledge and pathways for decision-making to facilitate sustainable development and thus partially paving the way for the transformation into socially integrative cities.

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