Monitoring Air Quality Using a Deep Learning Model

Shing Chiang TAN and Voon-Chet KOO

`

Abstract—Air pollution is a serious environmental issue that has negative impact on human health. With the rapid growth of urbanization and industrialization, many developing countries suffer from heavy air pollution. This article reviews air pollution problem and its impacts to health and the environment. Further, a novel deep learning-based air quality prediction method is presented. By monitoring air quality and understanding its changing trend, we can make prompt actions to protect our family and children.

Index Terms — Air Pollution, Air Quality Prediction, Deep Learning, Auto-encoder, Spatiotemporal Features

I. Introduction

AIR POLLUTION is one of the most serious problems in the world. It refers to the contamination of the atmosphere by harmful chemicals or biological materials. Both short and long-term exposure to ambient air pollution can lead to reduced lung function, respiratory infections and aggravated asthma. According to reports from the World Health Organization (WHO), air pollution is the cause of over 34% of deaths from stroke, lung cancer, and chronic respiratory disease, and 27% of deaths from ischaemic heart disease. The combined effects of ambient (outdoor) and household air pollution cause about 6.5 million premature deaths every year. Today, an estimated 92% of the world's population lives in areas where air pollution exceeds WHO safety limits.

A. *Types of Air Pollutions*

Air pollution is defined as the existence of certain pollutants in the atmosphere at levels that adversely affect human health or the environment. Pollutants with the strongest evidence for public health concern include particulate matter (PM), ozone (O_3) and nitrogen dioxide (NO_2). The health risks associated with particulate matter of less than 10 and 2.5 microns in diameter (PM_{10} and $PM_{2.5}$) is especially well documented. Think of PM as particles so light that they can float in the air. PM is capable of penetrating deep into lung passageways and entering the bloodstream causing cardiovascular, cerebrovascular and respiratory impacts. In 2013, PM was classified as a cause of lung cancer by WHO's International Agency for Research on Cancer (IARC). It is also the most widely used indicator to assess the health effects from exposure to ambient air pollution (WHO, 2016).

Another important pollutant posing serious risk to human health and the environment is ozone (O_3). Ozone may cause inflammation in the lungs and the bronchia. Once exposed to ozone, our bodies will try to prevent it from entering our lungs. This reflex reduces the amount of oxygen we inhale and makes our hearts work harder. For people already suffering from cardiovascular diseases or respiratory diseases like asthma, high ozone concentrations can be debilitating and even fatal. Besides, high levels of ozone corrode materials, buildings and living tissue. It reduces plants' ability to conduct photosynthesis, and hinders their uptake of carbon dioxide. It also impairs plant reproduction and growth, resulting in lower crop yields and reduced forest growth.

Nitrogen dioxide (NO_2) is another important air pollutant that has significant impacts on human health. NO_2 inflames the lining of the lungs, and it can reduce immunity to lung infections. Breathing air with a high concentration of NO_2 can irritate airways in the human respiratory system. Long-term exposure to NO_2 can aggravate respiratory diseases, particularly asthma, leading to respiratory symptoms such as coughing, wheezing or difficulty breathing. People with asthma, as well as children and the elderly are generally at greater risk for the health effects of NO_2. High levels of nitrogen dioxide are also harmful to vegetation – damaging foliage, decreasing growth or reducing crop yields.

Other important air pollutants are sulphur dioxide (SO_2), benzene (C_6H_6), carbon monoxide (CO), benzo(a)pyrene ($C_{20}H_{12}$), ammonia and heavy metals. Some of these pollutants have long-term effects on human health. For example, benzene can damage genetic material of cells and cause cancer in the event of long-term exposure. Besides, benzo(a)pyrene is a known cancer-causing pollutant. It is usually found in fine particles and it can also irritate the eyes, nose, throat and bronchial tubes.

B. Sources of Air Pollutions

Different pollutants are released into the atmosphere from a wide range of sources, including industry, transport, agriculture, waste management and households. Certain air pollutants are also released from natural sources. Some of these sources are discussed below:

Sources of Particulate matter (PM)

Examples of PM are fine solids or liquid droplets such as dust, fly ash, soot, smoke, aerosols, fumes, mists and condensing vapors that can be suspended in the air for long periods of time. These particles originate from a variety of sources and may be directly emitted (primary emissions) or formed in the atmosphere (secondary emissions) by transformation of gaseous emissions.

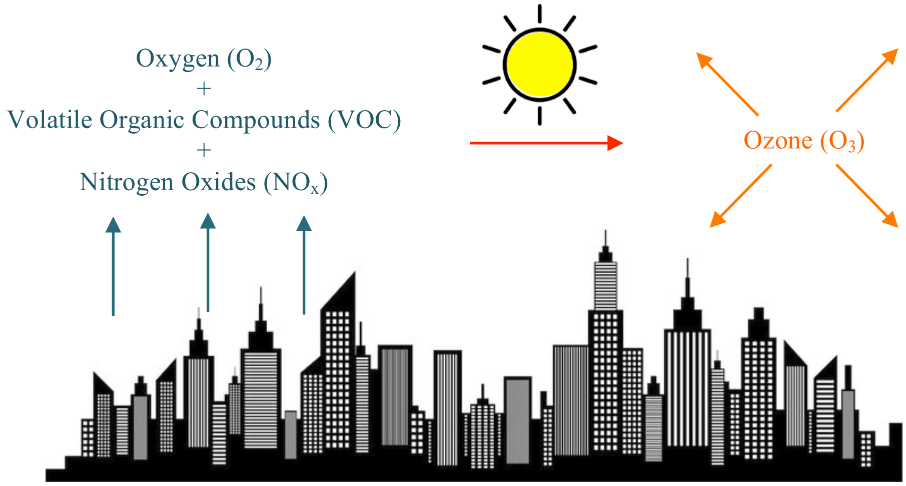
A significant portion of PM sources is directly generated from human (anthropogenic) activities such as industrial processes, agricultural operations, combustion of wood and fossil fuels, construction and demolition activities, and entrainment of road dust into the air. Natural (non-anthropogenic or biogenic) sources such as windblown dust and wildfires also contribute to the overall PM issue.

On the other hand, PM may form in the atmosphere as a result of complex chemical reaction between air pollutants such as SO_2, NO_2, and ammonia. These pollutants are considered precursors to PM formation and they are usually emitted from power plants, industries and automobiles. Control measures that reduce PM precursor emissions will have a beneficial impact on ambient PM levels.

Examples of Particulate Matter Generated due to Transport, Industry and Wildfire

Sources of Ozone (O_3)

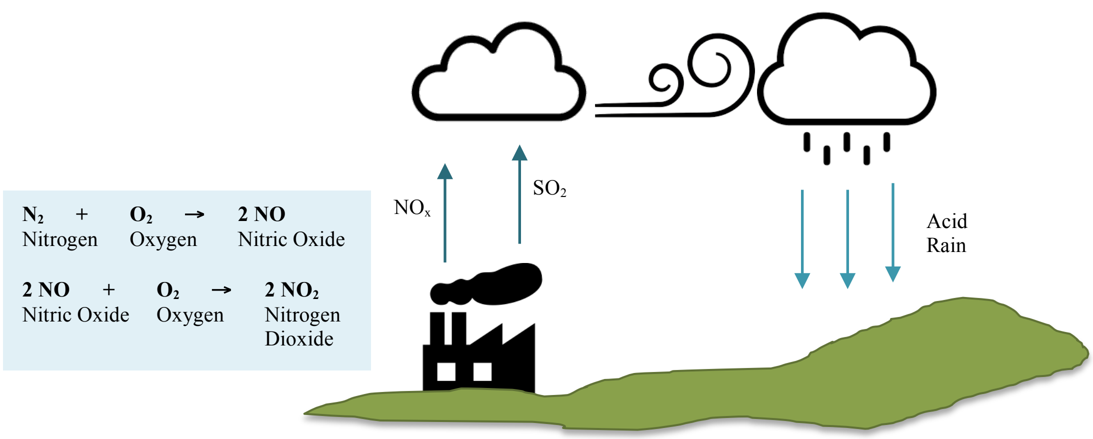
Ozone is present in two layers of the atmosphere. In the high layers of the atmosphere, ozone acts as a protective sunscreen that shields us from ultraviolet (UV) radiation coming from the sun. Ground-level ozone, however, can be harmful to humans, animals and plants. Ground-level ozone is not emitted directly into the air, but is created by photochemical reactions between precursor pollutants such as oxides of nitrogen (NO_x) and volatile organic compounds (VOC) in the presence of sunlight. This happens when pollutants emitted by cars, power plants, industrial boilers, refineries, chemical plants, and other sources chemically react in the presence of sunlight. As a result of its photochemical reaction, ozone exhibits strong seasonal patterns, with higher concentration in summer and in the afternoon. Ozone is most likely to reach unhealthy levels on hot sunny days in urban environments, but can still reach high levels during colder months. Ozone can also be transported long distances by wind, so even rural areas can experience high ozone levels.



Formation of Ozone

Sources of Nitrogen Oxides (NO_x)

Nitrogen oxides (NO_x) are toxic atmospheric pollutants. A natural source of nitrogen oxides occurs from a lightning strike. The very high temperature in the vicinity of a lightning strike causes the gases oxygen and nitrogen in the air to form nitric oxide (NO). The nitric oxide very quickly reacts with more oxygen to form nitrogen dioxide (NO_2). Similarly, when nitrogen is released during fuel combustion it combines with oxygen atoms to create nitric oxide. This further combines with oxygen to create nitrogen dioxide. Nitric oxide is not hazardous under ambient concentrations, but nitrogen dioxide is. Nitrogen dioxide and nitric oxide are referred to together as oxides of nitrogen (NO_x). NO_x gases react with sulfur dioxide (SO_2) to form smog and acid rain as well as being central to the formation of fine particles (PM) and ground-level ozone, both of which are associated with adverse health effects. In areas of high motor vehicle traffic, such as in large cities, the amount of nitrogen oxides emitted into the atmosphere can be very significant and have harmful impacts on human health and the environments.



Formation of Acid Rain by Emission of NO_x and SO_2

Other sources of air pollutants caused by human activities include burning of fossil fuels (coal, petroleum and other factory combustibles); agricultural activities (use of insecticides, pesticides and fertilizers); exhaust gases from vehicles, factories and manufacturing industries; mining operations; use of household cleaning products and painting supplies.

II. Air Quality Monitoring

In order to protect our family and children from being exposed to hazardous air pollutions, it is of great importance to monitor the air quality of our residential environment. Air quality is typically measured in the form of numerical values that track the state of the air pollutants over a period of time. Air quality can be measured and reported at different scales. For example, a city may track the air quality index of $PM_{2.5}$ and ozone level at various zones, so as to understand the severity of air pollution and to find the sources of pollutants within the designated areas.

Many air pollution data available today are taken from the nearest air quality monitoring stations, which could have poor data quality in terms of spatial and temporal resolutions. In order to better reflect the changing trend of air pollution and to provide up-to-date information for authorities to make prompt action, an intelligent environmental sensing and analytics solution, called *iEnviron*, is proposed [1]. In a typical *iEnviron* setup, a set of environmental sensors will be installed at the appropriate site location for continuous data collection. The environmental data such as air quality indicators (PM_{10}, $PM_{2.5}$, O_3 and NO_2) and weather-related indicators (ambient temperature, humidity, and rainfall) will be acquired on hourly basis and sent to a cloud server in real-time.

At the cloud server, the spatial and temporal environmental data will be fused and processed by an AI-based (artificial intelligent) data analytics engine. The air quality indicators are treated as a *spatiotemporal* process and a *deep learning* algorithm is used to construct a space-time prediction framework. Traditional linear-model methods such as auto regression moving average (ARMA) method is not suitable for air quality prediction, because air quality process is inherently nonlinear and its temporal trends and spatial distributions are greatly affected by various factors, such as air pollutant emissions and deposition, weather conditions and traffic flow. As compared to the traditional methods, the deep learning-based method uses multiple-layer architecture to extract nonlinear spatiotemporal air quality features, thus it has superior performance for air quality prediction.

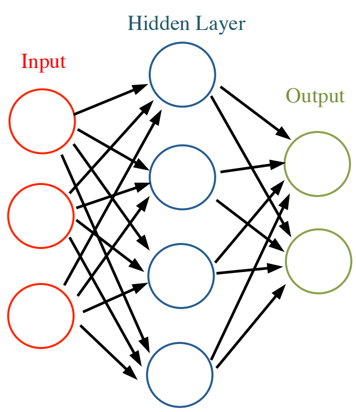
Overview of the *i-Environ* Solution for Air Quality Monitoring

A brief discussion on the novel deep learning model for air quality prediction is presented in next section.

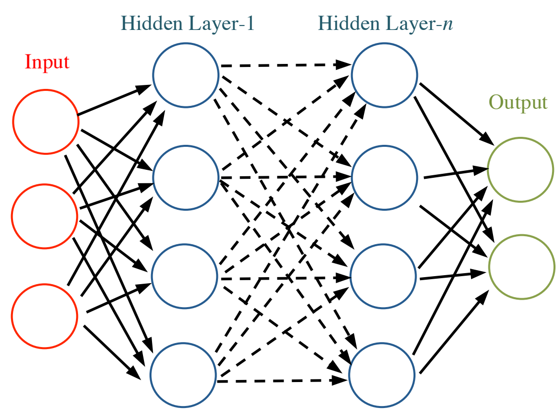
III. Deep Learning For Air Quality Prediction

A. *Overview of Deep Learning Architecture*

The idea of deep learning (DL) is inspired from artificial neural networks (ANNs). ANN is a popular research area of machine learning in the past decades. A classical ANN architecture consists of a single layer that performs nonlinear feature transformation. Unlike ANNs, deep learning techniques exploit multiple layers of nonlinear feature transformation, which are arranged in a hierarchical architecture, to construct and learn internal representation from a set of rich data. Multi-layer ANNs was first introduced in 1940s. However, conventional multi-layer ANNs always lead to a sub-optimal solution due to poor initialization points. A breakthrough on deep learning was made in 2006, where a new training method called layer-wise-greedy learning was introduced [2]. The layer-wise-greedy learning is based on an idea that unsupervised learning should be carried out before a training process begins in the next layer of the architecture. Upon retrieving features from the inputs, these features are fed to a subsequent layer where all samples are labeled and the network is fine-tuned with the labeled data. The unsupervised pre-training provides good initialization points to the network. Hence, the network can provide a better local optimal solution after the training process. In addition, the training session can achieve convergence in a faster rate.



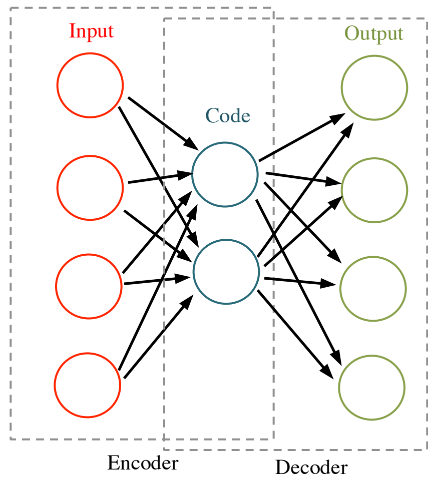
Artificial Neutral Network (ANN) Architecture



Deep Belief Network (DBN) Architecture

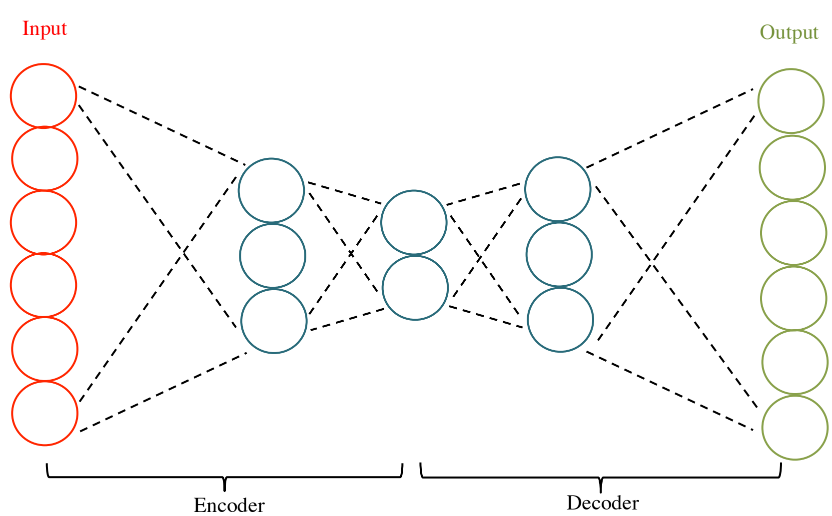
In recent years, various DL architectures have thrived [3] and have been applied in fields such as audio recognition, natural language processing, machine vision, where they have usually outperformed the traditional methods. *Deep belief network* (DBN), for example, is a popular DL architecture that consists of a layer of visible nodes and multiple layers of hidden nodes. All nodes are fully connected from one layer to another and no connection is established among nodes from the same layer. DBN employs the *Gibbs sampling* (a sampling method based on probability distribution) to train network parameters. DBN learns probability distribution with respect to inputs. Conditional probabilities are computed to determine the value of each node in the visible layer and also each node in the hidden layer. When the values of all hidden nodes in one hidden layer have been computed, all hidden nodes in the next layer will be updated. This update process is continued until convergence.

Another popular DL architecture is the *stacked autoencoders* (stacked AEs) [4]. The simplest form of an autoencoder (AE) is an ANN consisting of a single hidden layer. It employs an unsupervised learning algorithm to code the dataset. An AE learns to encode data from the input layer into a short code, and then decode it into something that closely matches the original data. This forces the AE to engage in dimensionality reduction, for example, by learning how to ignore noise. In other words, the AEs reconstruct the inputs in two stages. In the first stage, an input vector is converted to a representation in the hidden layer through an encoding operation, which involves a nonlinear transfer process from the input to the hidden layers. In the second stage, the AE reverts the representation in the hidden layer back to the original format of the data through a decoding operation, which involves a non-liner transfer process from the hidden to the output layers. During the training process, the difference between the original input and the reconstructed input is measured using an error function. The parameters in the hidden layer of the network are adjusted accordingly by referring to this error. The hidden layer provides extracted features (in a non-hierarchical format) to represent the inputs.



A Typical AE Architecture

A *stacked AE* is a deep learning model consisting of several AEs that are stacked together. It has been used for air quality prediction and obtained promising results [5]. This model provides a hierarchical representation for the inputs. The training process of a stacked AE is divided into two stages. In the first stage, the parameters of all hidden layers are updated through a series of unsupervised learning processes from left to right. In this case, the output from one hidden layer is the input used for training the parameters in the next hidden layer of the model. This operation is continued until the parameters of all hidden layers have been updated. All updated parameters from the first stage are used as the initial parameters of the stacked AEs for fine-tuning in the second stage. Labeled samples are included in the second stage. They are referred as supervised objects to refine the parameters from right to left layers of stacked AEs.

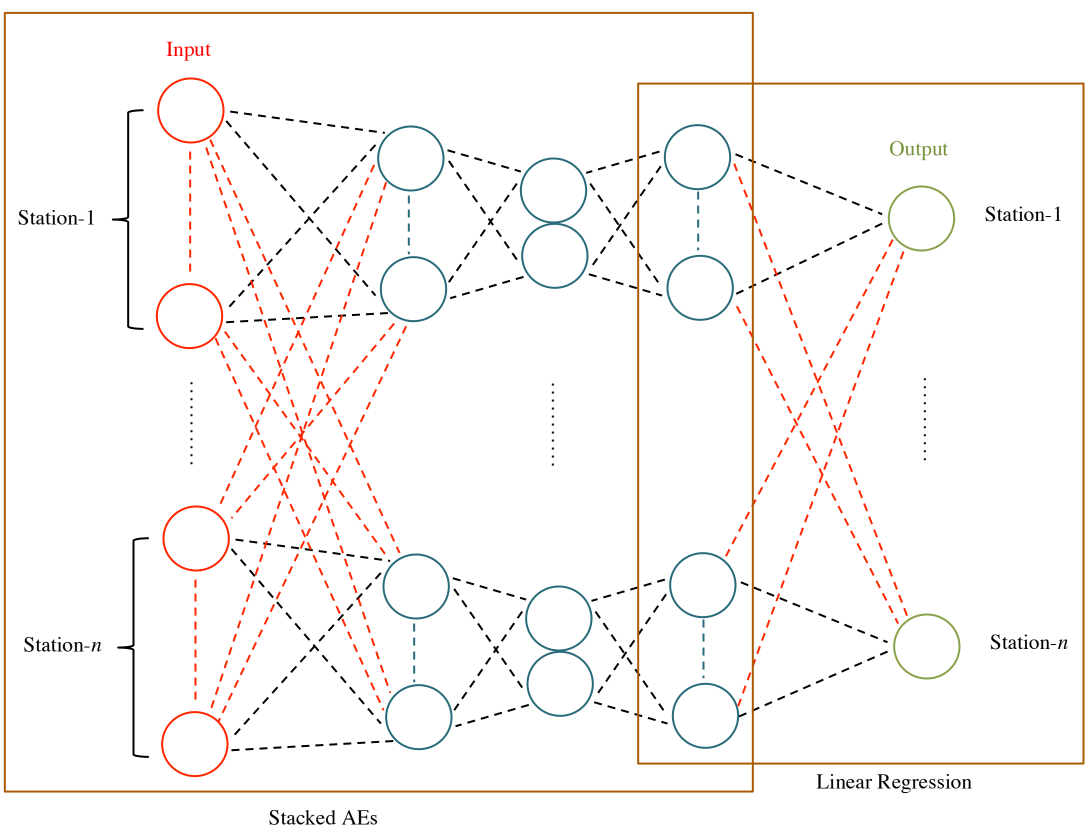


Stacked AEs Architecture

B. Stacked AE for Air Quality Monitoring

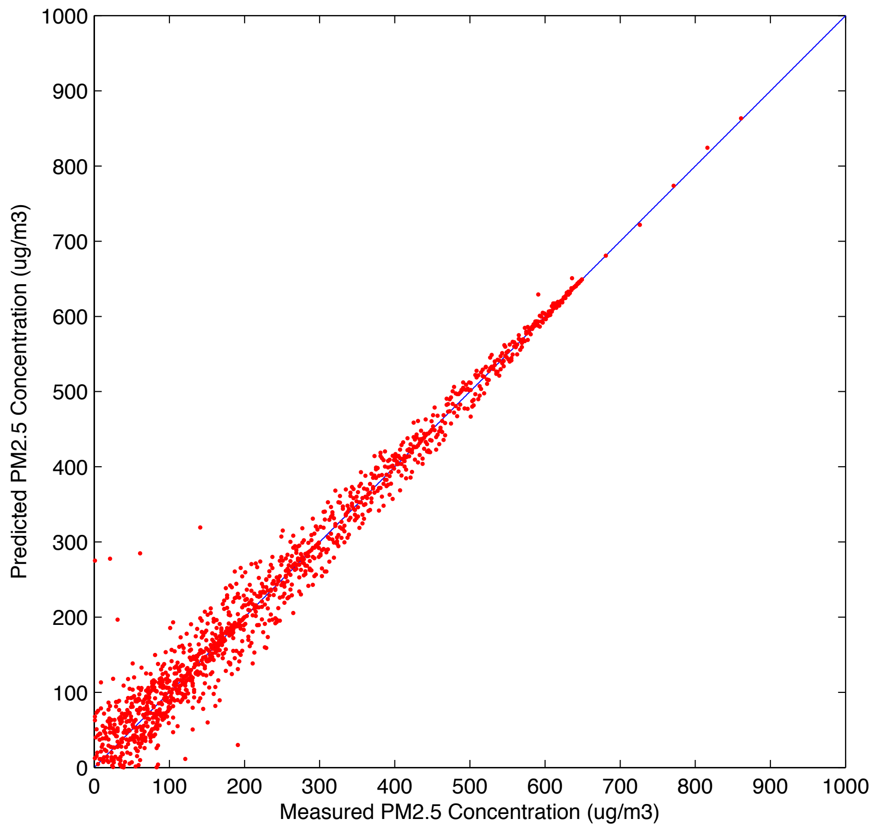
Figure below shows the design of a deep architecture for air quality monitoring. The air quality data, which include PM_{10}, $PM_{2.5}$, O_3 and NO_2, are collected from multiple *i-Environ* stations on hourly basis and sent to a cloud server in real-time. Besides, the weather-related indicators (ambient temperature, humidity, and rainfall) and the location information (GPS coordinates) of each station are also collected. The data from all stations are combined to train a set of stacked AEs. The combine data indicate the condition of air quality from a network of stations.

A stacked AE consists of L AEs (or layers). The first AE (layer) is trained using a time series data (such as $PM_{2.5}$ concentration for the past 24 hours) as the input. In this case, the air quality data from previous time intervals r together with those data at current time in all stations are used as the training data to predict air quality in all stations. The idea here is to construct a monitoring network that makes use of both spatial and temporal correlations to predict air quality concurrently in all stations. After the first layer has been trained, its output is utilized as the input to train another AE in the second layer. Likewise, the output from the second layer is the input for training an AE in the third layer and so forth. Hence, a set of sequential AEs can be stacked in a hierarchical architecture. Each current layer is deemed to represent a higher level of abstraction of its previous layer. A *greedy layer-wise unsupervised learning* is applied to pre-train the stacked AEs layer-by-layer from a left-to-right direction. To predict the concentration of $PM_{2.5}$, for example, a logistic regression is added to the right (i.e. the output) layer of the stacked AE to make real-value prediction. As the pre-training has been completed, a back-propagation algorithm is applied to refine all network parameters from a right-left direction.



Stacked AEs and Logistic Regression (LR) in a Deep Architecture for Air Quality Prediction

A sample of the prediction results for $PM_{2.5}$ concentration is shown in figure below, which indicates that the predicted data are closely matched with the measured data. It is observed that the deep architecture approach with unsupervised pre-training can effectively learn better air quality features than conventional time-series models. This is due to the fact that the stacked AEs have multiple-layer architecture that is capable of extracting nonlinear spatiotemporal correlation associated with the air quality features, thus improving the overall prediction performance.



Air Quality Prediction based on Deep Learning Architecture

IV. CONCLUSION

In this article, air pollution issue and its impacts to health and the environment are discussed. Particulate matter (PM), ozone (O_3) and nitrogen dioxide (NO_2) are among the strongest air pollutants that affect public health. These pollutants are released into the atmosphere due to many reasons, ranging from human activities (industrial processes, agricultural operations, combustion of wood and fossil fuels, etc.) to natural sources (windblown dust, wildfires).

It is of great important to continuously monitor, analyze and predict the air quality of our residential environment, so that we can make prompt action to protect our family and children from being exposed to hazardous air pollutions. *iEnviron* is an intelligent environmental sensing and analytics solution that can provide timely data (PM_{10}, $PM_{2.5}$, O_3 and NO_2) for air quality monitoring. It uses a novel deep learning-based method with multiple-layer architecture to extract nonlinear spatiotemporal air quality features. As compared to the conventional time-series methods, the deep architecture is more superior and can better predict the air quality with greater temporal stability.

REFERENCES

[1] Koo, V.C. (2018). *Monitoring Environmental Threats Through An Intelligent Sensing System*, i-Environ White Paper, March 2018.

[2] Hinton, G.E., Osindero, S., Teh, Y.W. (2006). A Fast Learning Algorithm for Deep Belief Nets, *Neural Computation*, vol. 18(7), 1527–1554.

[3] Y. LeCun, Y. Bengio, and G. Hinton (2015), Deep learning, *Nature*, vol. 521, no. 7553, pp. 436–444, May 2015.

[4] Zhang, Q., Yang, L.T., Chen, Z., Li, P. (2018). A Survey on Deep Learning for Big Data, *Information Fusion*, vol. 42, 146-157.

[5] Li, X., Peng, L., Hu, Y., Shao, J., Chi, T. (2016). Deep Learning Architecture for Air Quality Predictions, *Environment Science and Pollution Research*, vol. 23 (22), 22408-22417.