Chapter 19
Artificial Neural Network for Industrial and Environmental Research via Air Quality Monitoring Network

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ABSTRACT

Industrial and environmental research will always involve the study of the cause-effect relationship between emissions and the surrounding environment. The techniques of artificial intelligence such as artificial neural network can be applied in the industrial and environmental research. Chemical facilities have high risks to originate air emission events (e.g. intensive flaring and toxic gas release). They are caused by various uncertainties like equipment failure, false operation, nature disaster, or terrorist attack. Through an air-quality monitoring network, data integration is applied to identify the possible emission source and dynamic emission profiles. In this chapter, the above-mentioned application has been illustrated. It has the capability to identify the potential emission profile and characterize spatial-temporal pollutant dispersion. It provides valuable information for accidental investigations and root cause analysis for an emission event; meanwhile, it helps evaluate the regional air quality impact caused by such an emission event.

INTRODUCTION

Chemical facilities, where large amounts of chemicals and fuels are processed, manufactured, and housed, present high risks to seed potential air emission events. The normal emissions are those routine emissions that are expected during plant normal operations, which will have a large impact on the pollution concentration profile in the surrounding region. The air emission events may also be caused by severe process upsets due to planned operations such as plant scheduled turnarounds

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(start-up or shut down). Therefore,industrial and environmental research will always involve the study of the cause-effect relationship between the emission and the surrounding environment. For example, an olefin plant with ethylene productivity of 544,000 ton/yr can easily flare about 2,268 tons of ethylene during a single start-up(Xu, Yang, Liu, Li, Lou, Gossage, 2009), resulting in at least 18 tons of CO, 3.4 tons of NOx, and 45.4 tons of HRVOCs (defined in Texas air quality regulation as ethylene, propylene, isomers of butene, and 1,3-butadiene). If all the other flaring species (ethane, propylene, propane, and etc.) are also accounted, tremendous air emissions will be produced within a short-time period. Chemical plant emission events can also be caused by uncontrollable and unpredictable uncertainties such as emergency shutdown, nature disaster, or terrorist attack. For example, an oil refinery at eastern Japan exploded with huge amounts of toxic emissions due to Japan's tsunami and earthquake occurred on March 11th of 2011(NDTV, 2011). In another emission event on March 22nd of 2011, the blast of a carbide plant in Louisville, Kentucky, fired calcium carbide and produced a large amounts of inhalation hazardous gases (United States Chemical Safety Board, 2013).The air-quality impacts from chemical plant emission events can be serious to both local communities and their surrounding environments. One of the major concerns is the exposure of acute or short-term toxicity. Release of acutely toxic contaminants, such as SO2 and chlorine, would likely be transported to a populated area and pose an immediate threat to the public health and environment quality. Generally, the plant personnel should document and report emission details in response to an emission event, so that valuable information of hazardous releasing rate, possible transportation speed and directions, and potential harmful impacts on exposed populations and ecosystems can be estimated to support responsible decision makings. Since such responsible decisions are very critical, independent supporting information such as real-time measurements from a local air-quality monitoring network is vitally needed, especially in industrial zones populated heavily by various chemical facilities.

A local air-quality monitoring network can measure and record multiple pollutant concentrations simultaneously and alarm dangerous events in a real-time fashion. Meanwhile, based on measurement data from each monitoring station, plus regional meteorological conditions during the event time period, a monitoring network could help estimate possible emission source locations or even their emission rates. This inverse characterization of abnormal emission sources is very valuable to all stake holders, including government environmental agencies, chemical plants, and residential communities.

In the bulk of previous research, inverse modeling ideas were originated by the adoption of atmospheric dispersion models, which was normally used in the forward modeling problem to determine downwind contamination concentrations with given meteorological conditions and emission rates. "Gaussian Plume Model" is an approximate analytical method for point-source emissions for calculation of air pollutant concentration in the downwind area (Pasquill, 1961 and 1974; Turner, 1979 and 1994; Hanna et al., 1982; Seinfeld, 1986; Slade, 1986; Halitsky, 1989; Griffiths, 1994; Turner et al., 1989; Bowman, 1996). Even though inverse modeling methods based on Gaussian plume models have been reported(Hogan, Cooper, Wagner, and Wallstrom, 2005; Jeong, Kim, Suh, Hwang, Han, and Lee, 2005; MacKay, McKee, and Mulholland, 2006), they are generally used to estimate emission rates of point sources in an average long-time period based on measurements from multiple monitoring stations. It means their emissions are assumed under steady-state conditions and their values are treated as constants. Therefore, there is still a lack of studies on the reverse modeling for abnormal emission identifications with the consideration of dynamic emission rates of point emission sources.