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Information-based Network Environ Analysis for Ecological Risk Assessment of heavy metals in soils

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ABSTRACT

An information-based Network Environ Analysis (NEA) model coupled with fuzzy sets theory is developed and applied to a Thermal Power Plant (TPP) Ecological Risk Assessment (ERA) problem in this paper. Multiple sets of initial risk values are got by calculating different fuzzy evaluation grades of probability and then the advanced NEA model is applied to integrate the ecological risk of operation for the complex ERA of this soil ecosystem. The evaluation results show that the integral risk to soil microorganism can reach 1.6 times greater than the initial risk, while herbivores and carnivores (no initial risks) have to suffer 1/9 to 1/6 of vegetation's initial risks from external environment, and different probability distributions lead to multiple ERA results. This study quantified the multi-grade risks to entire system components and identified complex internal risk flow paths. The model is applied to multiple receptors with mutual ecosystem interference comparing to the existing one-fold risk evaluation and proved to be more comprehensive for ERA research in soils.

1. Introduction

Thermal Power Plants (TPPs) are one of the principal anthropogenic causes of hazardous volatile elements to the environment during electric power generation processes (Dragović et al., 2013). They discharge pollutants such as fly ash, slag washing water and flue gas, which accumulate in the surrounding environment and eventually lead to ecological risks. Ecological risk is defined as the environmental effects of certain stressors and their immediate and long-turn damage or harm to an ecosystem (Bai et al., 2011; Chen et al., 2013). Excessive deposition of heavy metals in soil may bring risks to ecosystems particularly when the content of trace metals is more than the background value and/or the tolerance level of receptors. As such ecological risks are uncertain, and the higher their level the more difficult in assessing the impact of the stressor, risk quantification and assessment become complicated especially in case of multiple pollutants simultaneously existing (Mandal and Sengupta, 2006; Tobor-Kapłon et al., 2007).

The complexity of ecosystem risk is driving a growing environmental modeling effort. A number of evaluation methods have been proposed for soil Ecological Risk Assessment (ERA) caused by heavy metals in various fields, such as mining, waste gas drainage, sewage irrigation (DeAngelis et al., 1989; Findlay and Zheng, 1999; Bartell et al., 1999; Lee and Lee, 2006; Pollino et al., 2007; Lu et al., 2008, 2009a,b; Chen et al., 2010; Schaubroeck et al., 2012; Chatterjee et al., 2015). Among the risk assessment methods that have been shown in previous studies, Network Environ Analysis (NEA) is new and important which is proved to be more suitable for the complex ecosystem risk. Network Environ Analysis (NEA) is one type of ecological network analysis evaluating and quantifying interaction chains and their indirect effects at the system level including pathway length (Patten, 1978a,b; Fath and Patten, 1999). For example, Gattie et al. (2006) analyzed seven-compartment, steady-state model of nitrogen flow in the Neuse River Estuary based on NEA and found two input environs and two output environs for analyzing network properties. With the decomposition of total system throughflow (TST), total environ throughflow (TET), total environ throughflow into compartmental boundary exchanges and environ flows, the fate of nitrogen entering the system and the origin of nitrogen leaving the system was analyzed and the importance of indirect effects was found. Whipple et al. (2007) discussed the indirect effects and distributed control in ecosystems by comparing environs from a time series of ecological networks with changing flow quantities. By studying the steady-state seasonal ecosystem networks and identify compartment that receives the 'analytical input' in output-environ analysis, macro-level analysis and micro-

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level analysis of whole environs was explored and differences in the seasonal networks analyzed was proved to be observed variation in environs. Fang et al. (2014) apply NEA to prove the existence of cycling and indirect flows in socio-economic water system and established an embodied socio-economic water system through the original network analysis for ecological systems. A risk-based network model based on a new control analysis termed control allocation and a conceptual conversion of flow currency in Network Environ Analysis (NEA) developed by Chen et al. (2011). By taking a river ecosystem intercepted by dam construction as an example, risk propagation between all functional guilds of the ecosystem concerning both direct and integral risk dynamics was quantified and illustrated in the network model.

Comparatively, NEA models may be more valuable, particularly for complex ecological risks caused by a variety of sources (even a variety of stress factors) on large-scale ecological receptors. The NEA places great emphasis on the interactions between components rather than the characteristics of individuals, and the dynamic attributes within the system are identified and quantified via network structural and functional analytic methods (Chen et al., 2011). An improved NEA has been proved as a complementary method for assessing disturbed ecosystems in the context of system-based management (Manickchand-Heileman et al., 2004).

In addition to the complexity, the uncertainty of the ecosystem risk is also constantly being studied. The uncertainty of the ERA exists in both the initial risk and the transmission of the indirect risk between different components in system. For the initial risk input, the ecological risk caused by heavy metal pollution is uncertain: on the one hand, there is no exact threshold value of existing assessment criteria for heavy metals ERA (Yang et al., 2016); on the other hand, the location of monitoring wells is often randomly selected which leads to the obtained pollution information to be used in ERA being varied with different selection schemes. Tran et al. (2002) developed a fuzzy decision analysis method for integrating ecological indicators, which combined fuzzy ranking method and analytic hierarchy process and was capable of ranking ecosystems in terms of environmental conditions as well as suggesting cumulative impacts across a large region. Chen et al. (2010) coupled fuzzy sets theory with Monte Carlo analysis to provide a stochastic simulation of pollutant dispersion for assessing environmental risks associated with produced water discharges. For the indirect risk transfer, a new concept *IU* (indirect uncertainty) analysis was defined and applied by Chen and Chen (2012) in the system-based ERA through qualitative reasoning, which is considered as a necessary complement for the disposal of uncertainty on the system scale.

However, only using the traditional NEA method to solve the complexity of ecological risk as well as the fuzzy or *IU* method to solve the uncertainty is far from enough. It is necessary and meaningful to find a coupling method that can solve the complexity and uncertainty at the same time. Firstly, Energy and material, the regularly used mediates for network deduction, are not substantially accommodated for a system-wide ERA. So it is necessary to explore an information-based NEA method. Secondly, considering heavy metal concentrations in different fuzzy evaluation standards of probability, and then getting multiple sets of initial risk values, on the basis of which using NEA to integrate the ecological risk of operation may be an applicable solution for complex ERA problems.

Therefore, this research aims to couple fuzzy sets theory with an improved NEA method for soil ERA. The proposed approach is capable of evaluating potential influence of various risk stressors via direct and indirect paths associated with heavy metals transferring in TPPs surrounding regions. Different from the previous study, the calculation results of the probability of interference occurrence ($\tilde{P}_x$) in our study are multiple fuzzy values rather than a fixed one. For centralized monitoring values, the probability distributions are better to be identified according to stricter environmental standards with more grades. Multiple sets of initial risk values are got by calculating different fuzzy evaluation grades of probability and transfer into multiple sets of integral risk values at last combined with the multiple direct risk through the NEA model. That is to say, the fuzzy theory is applied throughout the whole NEA method, which transform a general network model into a fuzzy one. This improved method broads the existing one-fold risk evaluation to comprehensive and networked one as well as reveals risk transfer pathways of multiple receptors with mutual ecosystem interference. What's more, it can reveal the laws of risk transfer flow, and quantify the overall risk of multiple sources to major components in the entire ecosystems.

2. Methodology

2.1. Calculation of risk flow

The NEA, as an important branch of network analysis, is a system-oriented modeling technique for examining the structure and flow of materials in ecosystems (Patten, 1978a,b, 1982; Leontief, 1951, 1966; Hannon, 1973; Christian et al., 2009). Risk flow is not an energy or mass based interaction but an information one.

The simulation of risk flow via direct pathway is based on network control allocation (*CA*). Network control is characterized as the ratio of pair-wise integral flows using network flow and storage analysis, and represents the control each component exerts in the overall system. Metrics called the control difference and control ratio were used to describe the absolute open-loop control relationships between components Schramski et al. (2006, 2007). Combining these two measures, the control allocation (*CA*) method was further developed as a modified version of the distributed control index among components. Among all interactive compartments, CA can reveal the effect of one compartment exerting on another. Input risk of compartment *i* from the external environment is transferred to compartment *j* through CA. CA calculates a control strength between components; dominant factor information is allocated and dispersed as follows:

$$CA = (ca_{ij}) \begin{cases} ca_{ij} = \dfrac{n_{ij} - n'_{ji}}{\sum_{i=1}^{n} (n_{ij} - n'_{ji})} & n_{ij} - n'_{ji} > 0 \\ ca_{ij} = 0 & n_{ij} - n'_{ji} \leq 0 \end{cases} \tag{1}$$

$$N = (n_{ij}) = G^0 + G^1 + G^3 + \cdots + G^m + = (1 - G)^{-1} \tag{2}$$

$$N' = (n'_{ij}) = (G')^1 + (G')^2 + (G')^3 + \cdots + (G')^m = (1 - G')^{-1} \tag{3}$$

$$G(G') = [g_{ij}]([g_{ji}]) \tag{4}$$

$$g_{ij}(g_{ji}) = \frac{f_{ij}}{T_j} \left(\frac{f_{ij}}{T_i} \right) \tag{5}$$

where f_{ij} denotes energy/material flow from j to i; T_i (or T_j) is the sum of flows into or out of the ith (or the jth) compartment, which is the accumulation of the energy values of each row (or column) in the energy matrix. The risk information is transmitted and interpreted among components via the input/output environment once the ecosystem is exposed to specific disturbance. Direct flows and indirect interactions are considered to explore the integral risk flow scenario, with the pathway length being 1 (for direct risk pathways) or more than 1 (for indirect risk pathways).

2.2. Risk flow mechanism in NEA

Ecological risks arising from heavy metals discharged by TPPs are transferred and diffused throughout the system components.