Journal of Loss Prevention in the Process Industries 56 (2018) 262–271

Contents lists available at ScienceDirect

Journal of Loss Prevention in the Process Industries

journal homepage: www.elsevier.com/locate/jlp

Application and improvement of swarm intelligence optimization algorithm in gas emission source identification in atmosphere

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ARTICLE INFO

Keywords:
Gas leakage
Hazard identification
Swarm optimization
Inverse problem
Emission source estimation

ABSTRACT

Hazardous gas emissions could cause serious consequences for ecology, environment, human life and even society. Thus gas emission source term identification is crucial for emergency response and safety management. Based on experimental data, swarm intelligent optimization (SIO) algorithms including particle swarm optimization (PSO), ant colony optimization algorithm (ACO) and firefly algorithm (FA), are compared to identify the gas emission source parameters including source strength and location parameters. The results show that all three SIO methods used in this work have similar performances in terms of source parameter estimation, and all of them depend slightly on initial range set for individuals in the population. However, PSO method is superior in computational efficiency compared with ACO and FA methods. The convergence rate of FA is faster than that of ACO. PSO method can obtain satisfied estimation results under different boundary constraints, while the estimation results of FA and ACO will become unrealistic under too wide boundary constraints. The impact of atmospheric conditions on estimated results is also discussed. The results under extreme atmospheric conditions are worse than that in other conditions. Finally, SIO method coupled with a new model, correlated matching of concentration distribution (CMCD) model, is applied to the source location estimation. Test results prove that SIO-CMCD model can obtain a satisfied estimation as well as greatly enhanced computational efficiency when only location parameters are required to be determined. Hence, SIO is a useful tool to estimate emission source term for the storage and transportation process of hazardous gas or volatile materials.

1. Introduction

More and more hazardous materials are used in different industries and thus potential risks caused by these dangerous sources are very high. Emission of flammable hazardous materials, such as oil and gas products, from storage or during the transportation process, could lead to serious consequences. Hence, it is very important to monitor and trace the emission source for risk assessment and control (Safitri et al., 2011; Li et al., 2016; Ma et al., 2018a; 2018b). Source parameters identification is a basic way to trace the source term. The estimated results of source parameters such as location and strength can be utilized to analyze, manage and control the risk and then reduce the loss caused by an emission event.

Currently, compared with the direct method of source determination using a portable instrument, more attention has been paid to the source identification method combing monitor data and inverse algorithms. For a forward process, the gas concentrations distribution is predicted with forward dispersion model while the source term is estimated with inverse problem model for inverse process. Various methods have been employed to identify source terms, such as stochastic probability method based on Bayes inference (Hirst et al., 2013; Yee et al., 2014; Ma et al., 2014; Xue et al., 2018), inverse Langrangian stochastic model (Flesch et al., 2004) and optimization method (Haupt, 2005; Ma et al., 2013; Wang et al., 2018). Among these methods, optimization algorithm is widely used due to its high efficiency and accuracy as well as the capability of multiple parameters estimation.

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https://doi.org/10.1016/j.jlp.2018.09.008
Received 24 May 2018; Received in revised form 14 September 2018; Accepted 15 September 2018
Available online 17 September 2018
0950-4230/

Many different optimization algorithms including classic optimization methods (e.g. simplex, pattern search, convex optimization) and heuristic algorithms (e.g. genetic algorithm (GA) and simulated annealing (SA)), have been applied to identify source parameters and reconstruct source terms under different environments. For classic optimization methods, it is fast to estimate the source parameters, but these methods always depend on the initial values and are often restricted near the local optimization point (Ma et al., 2013). Therefore, global optimization method is adopted to obtain the source parameters for the problem of gas emission. Heuristic optimization methods are able to find global optimization values, and thus have been tested to estimate source term. Among them, swarm intelligence algorithm (SIA) is proposed based on simulating the intelligent behavior of the biotic population to solve the complex optimization problems (Chu et al., 2011; Pan et al., 2011; Ni et al., 2013). However, emission source estimation with SIA has not been discussed comprehensively.

Particle swarm optimization (PSO), ant colony optimization (ACO) and firefly algorithm (FA) are three typical group optimization algorithms. PSO algorithm is inspired from the foraging behavior of bird groups. It is often used to deal with some complex and nonlinear problem (Pan et al., 2011; Ma et al., 2017, 2018c). ACO is developed based on the food-finding behavior of groups of ants, which takes a distributed parallel operation mechanic (Ni et al., 2013; Qin, 2013). ACO is robust and adaptable, which makes it easy to combine with other algorithms. FA evolves from the information communication mechanism by fluorescence among fireflies (Fister et al., 2013; Bhushan and Pillai, 2013; Yelghi and Köse, 2018). FA can find an optimization solution easily for multi-modal function. For gas emission source estimation with SIA methods, only PSO was reported to identify gas emission sources. Moreover, the performance and influence factors of different SIA methods have not been quantitatively discussed for emission source identification. Additionally, how to improve the computational efficiency of source estimation method with SIA is also a challenge in this field.

In this work, different kinds of SIA methods will be utilized to identify the source parameters, and then the performance and property of different methods will be compared quantitatively with each other. Then, a new estimation function based on a correlated matching of concentration distribution (CMCD) method will be proposed to improve the location estimation performance with SIA methods.

2. Mathematic model

2.1. Object function

The basic object function adopted here is shown in Eq. (1) (Haupt, 2005; Long et al., 2010).

$$\min f_0 = \sum_{i=1}^{N} [C_{\text{mea},i} - C_{\text{pre},i}(Q, x, y, z)]^2$$
$$\text{s.t.} Q > 0; x > 0; -\infty < y < \infty; \tag{1}$$

where $C_{\text{mea},i}$ (g m^{-3}) is the concentration measured by the sensor at the position i and $C_{\text{pre,i}}$ (g m^{-3}) is the concentration predicted by the forward dispersion model; Q is the emission source strength (g s^{-1}); x, y and z are downwind, crosswind and vertical distances of the sensor to the source location respectively (m). N is the number of the measurement. The source of Eq. (1) is assumed to be on the position of $x = 0$ and $y = 0$. f_0 is the object function, which means the error between measurement and prediction.

2.2. Forward dispersion model

Forward dispersion model is a dominant factor for source estimation problems. Many different dispersion models, including computational fluid dynamic (CFD) (Vázquez-Román et al., 2016; Efthimiou et al., 2017), Lagrangian stochastic (LS) (Flesch et al., 2004), Gaussian dispersion model (Ruj and Chatterjee, 2012; Ma et al., 2014; Li et al., 2015) and machine learning network model (Ma and Zhang, 2016), have been applied to solve inverse problems of source term identification. Among these forward models, Gaussian model is a classic one based on experiments and solution of dispersion equations, which is widely used for point source estimation in atmosphere for its high computational efficiency and satisfied accuracy. Here, Gaussian dispersion model is also selected as the forward dispersion model for a continuous point emission, which is expressed in Eq. (2) (Briggs, 1973).

$$C = \frac{Q}{2\pi U\sigma_y\sigma_z}\left\{\exp\left(\frac{-(z-h)^2}{2\sigma_z^2}\right) + \exp\left(\frac{-(z+h)^2}{2\sigma_z^2}\right)\right\}\left\{\exp\left[\frac{-y^2}{2\sigma_y^2}\right]\right\} \tag{2}$$

Here, C (x, y, z) is the concentration at the position of (x,y,z) in atmosphere. U is the wind speed (m s^{-1}) and h is the effective height of the emission source. σ_y (m) and σ_z (m) are the distance deviation coefficients in crosswind and vertical direction, which are related to the downwind distance and atmospheric condition. In this research, σ_y (m) and σ_z (m) are determined by the formulas recommended by Briggs (1973).

3. Principle of algorithms

3.1. Particle swarm optimization

Particle swarm optimization (PSO) algorithm is a method based on the foraging process of bird swarms, which finds an optimization route with the collective coordination. During the process of PSO, every optimization problem is viewed as a particle with an adaptive value determined by the optimization function in the search space to judge the status of the particle at this position. Each particle is able to find an optimized position and velocity with the memory at a certain position to decide the direction and distance for the next step. The calculation process can be depicted as following:

First, the particles are initialized with the random position and velocity in a feasible region and the adaptive value of each particle is calculated with adaptive function. Then, the particle's adaptive value is compared with local optimization solution (pbest) and global optimization solution (gbest), and the best values are updated with the best solution. Finally, every particle's position and velocity are updated with the above process until the termination condition is satisfied.

The adaptive function is set as $F(x)$ and the number of the total particles is m. The dimension of search space is D. The position of ith particle can be expressed as $x_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$, and its velocity $v_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$. The first generation x_i is produced randomly and then it is introduced to the adaptive function $F(x)$. The optimized position of particle i passed is $p_i = (p_{i1}, p_{i2}, \ldots, p_{iD})$ and the optimized position of all particles passed is, which is the global optimization value in the current step. The position and velocity for every particle is updated with Eqs. (3) and (4):

$$v_{id}^{t+1} = v_{id}^{t} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}) \tag{3}$$

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \tag{4}$$

where, $i = 1,2, \ldots,m$; $d = 1,2, \ldots,D$. c_1 and c_2 are acceleration factors; r_1 and r_2 are two random numbers (Kennedy and Eberhart, 1995).

The computation process of PSO algorithm is illustrated in Fig. 1.

3.2. Ant colony optimization

The food-finding process of an ant colony is depicted as following: each ant begins to find food with random position and velocity, and the pheromone is released on the road passed before. The pheromone will accumulate more on the shorter path during the same time period, and then more ants will choose this path (Dorigo et al., 1996; Homsup, 2016). Some ants may find another new way with shorter distance than