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Application of Particle Swarm Optimization (PSO) algorithm for Black Powder (BP) source identification in gas pipeline network based on 1-D model

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Abstract. Black Powder (BP) is a worldwide challenge that spans all stages of the natural gas industry from the producing wells to the consuming points. It can endanger the pipeline operations, damage instruments and contaminate customer supplies. The formation of BP inside natural gas pipeline mainly results from the corrosion of internal walls of the pipeline, which is a complex chemical reaction. This work aims to develop a novel algorithm for BP source identification within gas pipelines network based on a 1-D model of BP transport and deposition. The optimization algorithm for BP source identification is developed based on the well-known Particle Swarm Optimization (PSO) algorithm, which can solve constrained optimization problems. By applying this optimization algorithm on the gas transmission pipeline network, the BP source at different junctions could be identified and quantified simultaneously. Extensive simulation studies are conducted to validate the effectivity of the optimization algorithm.

1 Introduction

With the wide use of natural gas, it is challenging to maintain operational efficiency and safety for gas transmission pipeline network, which is a complex system with pipeline length varying from hundreds to thousands of kilometers (Banda *et al.*, 2006; Tobin and Shambaugh, 2006). Black Powder (BP), occurring in both liquid and gas pipelines, is the name given to the black particulates and sediment found in pipelines. It is mainly generated due to the chemical reaction of H_2S, water and iron, resulting in a mixture of fine particle corrosion product and other solids, such as sands, clays, metal or construction debris, and liquid hydrocarbons chemically incorporated with any quantity of iron sulfide, iron carbonate and iron oxide contamination (Khan and Alshehhi, 2015; Khan *et al.*, 2015; Sherik *et al.*, 2008; Sherik, 2008; Trifilieff and Wines, 2009). Although there exist various compositions of BP, they possess some common characteristics, for example, adsorption, high specific gravity and difficult to clean. In terms of BP generation, they could come from the gas source in the gas field and also result from movement of the upstream point with gas flow, which originates from the corrosion of internal wall of any pipeline. Specifically, corrosion could only occur in the pipeline with the flow of “wet” gas (Beavers and Thompson, 2006; Baldwin, 1998), which is natural gas mixed with a certain amount of water, providing a necessary condition for corrosion. The presence of BP in gas pipeline network threatens the safety of gas industry and also has lots of undesirable influence on the operating companies all over the world (literature reviews of Khan and Alshehhi, 2015). First of all, the gas quality will be greatly affected by intolerable concentration of solid particles. Secondly, gas transmission cost will gradually increase, resulting from raised pressure drop due to changes of internal wall roughness and diameter over a long time of operation. Thirdly, the contaminations of BP could cause compressor failures, erosion of control valve and instrument clogging, etc. (Baldwin, 1998). Finally, the cleaning/removal of BP and frequent replacement of customers’ cartridge filter elements could increase the expenses each year.

To reduce the influence of BP on gas industry, many companies attempted to manage and control the BP in gas transmission pipeline network. In general, the existing methods could be classified into two different aspects (Al-Qabandi *et al.*, 2015; Cattanach *et al.*, 2011; Khan *et al.*, 2015; Trifilieff and Wines, 2009; Tsochatzidis and Maroulis, 2007): (1) BP removal and (2) prevention methods. The approach of removing BP from gas transmission pipeline is successful in several respects, including increasing operational safety, altering operational parameters, increasing operational efficiency and facilitating effective corrosion inspection. If BP problem is not serious (small quantities), mechanical cleaning is widely used for most of the pipelines.

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Normally, mechanical scrapers are used to clean pipeline wall, such as mechanical pigs are deployed into a pipeline to scrape debris from pipeline wall and remove BP. Although mechanical scrap is efficient to keep the pipeline in fairly clean condition, frequent cleaning could damage the pipeline wall by exposing fresh steel surface under "wet" gas, resulting in excessive corrosion and BP generation. In addition, mechanical cleaning is not effective with complex BP formation, which calls for a combination of chemical cleaning. It has been practiced that chemical cleaning, acting as liquid soap, could significantly improve the efficiency of BP removal combined with mechanical cleaning, such as pigging operations, which acts as brush (Trifilieff and Wines, 2009). Separators and cyclo-filters are also widely installed to reduce the BP concentration, where these devices could physically knock out the BP particles in the gas stream. Then, the BP particles are collected at the bottom in a collection hub. However, this method only applies to gas stream with a high concentration of solid particles and also relatively large particle size (more than 10 microns). The removal approach is practiced as a good option to protect the downstream operations, but it has several disadvantages (Trifilieff and Wines, 2009). These methods are not single trial, but frequent application, which account for a large amount of expense. Also, these solutions cannot address the location of BP formation, that is to say, they are afterward remedy. In addition, chemical cleaning needs subsequent handling procedures, which could be costly and challenging if the chemical disposal is toxic or harmful to the environment. To compensate the above drawbacks of removal approach, gas operators have an alternative solution to prevent the occurring of BP generation, which is considered as a consequence of corrosions at the internal wall of gas transmission pipeline (Cattanach *et al.*, 2011; Trifilieff and Wines, 2009). To prevent the occurring of corrosions, the inner wall of gas transmission pipeline is normally coated with high solids solvent-based epoxy polyamine films, which is used to protect the inner surface of pipelines. This approach is practiced to be cost effective; however, it is difficult to be applied to buried pipelines. Reducing water contamination is another approach to prevent the occurring of pipeline corrosions, which is based on the philosophy of internal corrosions, are largely related to the case of "wet" gas. Namely, this approach is moisture control.

Although several removal and prevention methods have been put into practice, the location of BP generation is still unpredictable and there is no research on the identification problem of BP source until now. The main reason is the unknown information about the BP generation and where it could be generated. The developed dynamic models for BP transport and deposition are limited for gas transmission pipeline network, which in turn restricts the study of model-based methods for BP identification. It is well known that full three-dimension (3-D) Computational Fluid Dynamics (CFD) simulation software is specialized for multiphase flow modelling; however, it seems impossible to simulate the 3-D dynamics of large pipeline networks (*e.g.* 100 km), which is under studied in these works (Kharoua *et al.*, 2015, 2017). Filali *et al.* (2016) proposed a 1-D approach for modelling transport and deposition of BP particles in gas transmission network, where the authors discussed behaviors of particles with different diameters. Moreover, two different deposition models (Fan and Ahmadi, 1993; Wood, 1981) were compared to calculate the bed height, which was validated by Discrete Phase Model (DPM) based on CFD software.

The main contribution of this work is to develop a tool to identify the BP source in gas pipeline network, which is modeled as tree-shaped gas transmission network with BP dynamics of motion and distribution along each pipe. BP source identification is formulated as a constrained optimization problem, which is solved by the Particle Swarm Optimization (PSO) techniques (Delice *et al.*, 2017; Eberhart and Shi, 1998; Kennedy and Eberhart, 1995; Min *et al.*, 2017). PSO is a popular stochastic optimization technique with some features and advantages compared to other optimization algorithms such as Ant Colony Optimization (ATO) and Genetic Algorithm (GA) (Wiak *et al.*, 2008; Saravanan, 2006). These features and advantages include (1) taking real numbers as particles; (2) few parameters need to be tuned and (3) simple implementation and effective global search capability, hence it could be a good candidate. In fact, PSO technique has been widely used in oil and gas industry, for example, Wu *et al.* (2014) optimized the operation of trunk natural gas pipelines *via* PSO based algorithm, and Madoliat *et al.* (2017) also successfully applied PSO to the transient analysis of natural gas pipeline. The PSO algorithm is used to solve a formulated optimization problem for similar applications. In particular, the basic PSO algorithm has been improved by incorporating the inertia-adaption technique to solve a constrained nonlinear optimization problem in Wu *et al.* (2014). Then, it was used to solve a more complex problem in Madoliat *et al.* (2017), where the solution of nonlinear PDE flow equations could be obtained simultaneously.

The paper is structured as follows. Section 2 will briefly discuss the 1-D approach for modelling BP particles in gas networks, which is detailed in Filali *et al.* (2016). A general structure of tree-shaped model of gas transmission pipeline network is given. In Section 3, PSO-based optimization algorithm for BP identification is presented. In Section 4, extensive simulation results and discussions of the optimization algorithm for BP source identification are presented. Finally, conclusions are given in Section 5.

2 Modelling for dynamics of BP particles in gas transmission pipeline

In this section, a schematic of tree-shaped gas transmission pipeline network will be built based on a set of pipeline connection rules. In addition, the methodology of a 1-D approach for modelling the dynamics of transport and deposition of BP particles in the gas pipeline network will be explained (Filali *et al.*, 2016).

2.1 A tree-shaped model of gas network

In gas industry, the natural gas pipeline network is a highly integrated transmission and distribution grid that could transport natural gas from its origin to any position of high gas consumption demand. In many cases, the natural gas produced from a well has to be transported on a very long distance to the point of use. In order to maintain effective distribution of natural gas, the gas transmission system is extensive, consisting of complex pipeline topology. However, the entire gas transmission network could be separated into several sub-network with single gas well. This simplification also contributes to the investigation of BP identification, which will be included in following sections of this paper. In this case, the gas transmission pipeline network is properly generalized as tree-shaped model (Babonneau *et al.*, 2012; Shiono and Suzuki, 2016), which could be built based on following rules for pipe connection:

1. Gas transmission pipeline network without loop;
2. Junction connected with three pipes;
3. One-way flow of gas stream.

Based on these connection rules, a schematic of tree-shaped gas pipeline transmission network is given in Figure 1. There is only one source for gas supply, and each junction has three pipe connection, including two main pipes and one branch pipe. The arrow on the pipe shows the flow direction of gas stream. The customer is located at the end of each branch pipe. The sources, main pipes, branch pipes and customers are denoted as S, P, B, and M respectively.

2.2 One-D approach of modelling BP particle dynamics

In this section, the 1-D approach for modelling dynamics of BP particles in gas pipeline (Filali *et al.*, 2016) is described. It is well known that the CFD software is popular to simulate the dynamics of multi-phase flow, which could give a solution to the simulation of BP particles in the gas stream. However, the computation load of CFD is extremely heavy for gas pipeline network, which could extend to hundreds of kilometers. In this case, Filali *et al.* (2016) proposed a simplified 1-D approach of modelling, where the flow of gas is continuously mixed with BP particles, and the behavior of particle movement is modelled based on the dusty gas assumption and the usage of analytical solutions of steady scalar advection/reaction equation.

The governing equation for gas stream mixed with solid particles is given by the following one-dimensional advection–diffusion-reaction equation:

$$\frac{\partial C}{\partial t} + U\frac{\partial C}{\partial x} = D_{\mathrm{diff}}\frac{\partial^2 C}{\partial x^2} + S, \tag{1}$$

where C is the particle concentration in the gas flow, U is the average velocity of gas flow inside the pipeline, D_{diff} is the diffusion coefficient, S is a term to describe the deposition, pickup or generation of solid particles. For fully developed turbulent flow, the axial diffusion term $D_{\mathrm{diff}}\frac{\partial^2 C}{\partial x^2}$ is negligible compared to the dominant advection term $U\frac{\partial C}{\partial x}$ and the following expression is valid,

$$D_{\mathrm{diff}}\frac{\partial^2 C}{\partial x^2} \ll U\frac{\partial C}{\partial x}. \tag{2}$$

For steady state solution, equation (1) could be simplified as:

$$U\frac{\partial C}{\partial x} = -\beta_{\mathrm{dep}}C + \xi_{\mathrm{gen}}, \tag{3}$$

where, β_{dep} is the deposition rate and it could be calculated based on two methods, for example, Wood (1981), Fan and Ahmadi (1993), and ξ_{gen} is the generation rate of the BP inside the pipeline and it is considered as an unknown parameter.

3 PSO-based optimization algorithm for BP identification

In this section, the objective of BP identification is presented as a constrained optimization problem, which will be solved by a PSO-based optimization algorithm. The PSO algorithm is a population-based evolutionary search algorithm inspired by social behavior of animals such as bird flocking. Basically, each particle in the swarm has a position and velocity, with its position representing a candidate solution in the multi-dimensional solution space and velocity indicating moves from one position to another. A fitness function is defined to evaluate each particle until certain convergence criteria is satisfied. During the searching process, the particle with fitness value will be selected as local/global best particle. The updated equations of position and velocity are given in the literature (Marini and Walczak, 2015) as follows:

$$x_{\mathrm{ij}}(t+1) = x_{\mathrm{ij}}(t) + v_{\mathrm{ij}}(t+1), \tag{4}$$

$$\begin{aligned} v_{\mathrm{ij}}(t+1) = v_{\mathrm{ij}}(t) + c_1 r_{1j}(t)\left[y_{\mathrm{ij}}(t) - x_{\mathrm{ij}}(t)\right] \\ + c_2 r_{2j}(t)\left[\hat{y}_j(t) - x_{\mathrm{ij}}(t)\right], \end{aligned} \tag{5}$$

where, $x_{\mathrm{ij}}(t)$ denotes the position of particle i in dimension j at time t, with $j = 1, 2, 3, \ldots, n_x$, and n_x is the dimension of the solution space. The updating of position is calculated by adding the velocity $v_{\mathrm{ij}}(t)$ to current position. $y_{\mathrm{ij}}(t)$ is the personal best solution in dimension j for particle i, while $\hat{y}_j(t)$ represents the best solution found so far. c_1 and c_2 are positive acceleration factors used to scale the contribution of cognitive and social component. r_{1j}, $r_{2j} \in [0, 1]$ are random variables with normal distribution.

The structure of this section is outlined as follows: firstly, the objective of BP identification is formulated, which is developed based on the 1-D model of BP particles transport and deposition. Secondly, the BP source could be identified and quantified by sole running of the PSO-based optimization algorithm. Finally, a proof will be provided to support the uniqueness of the formulated optimization problem.

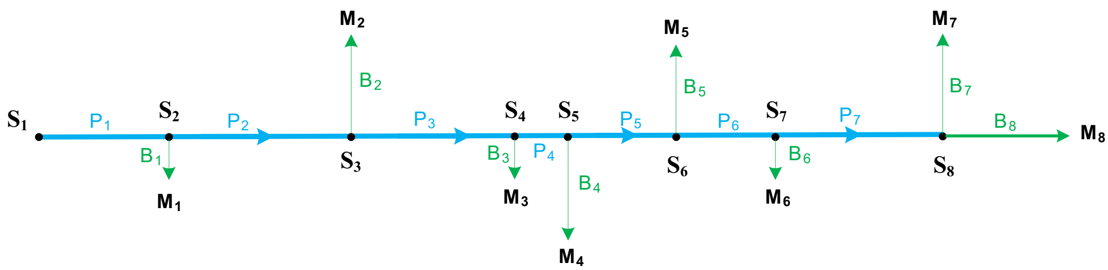


Fig. 1. Schematic of gas transmission pipeline network.

3.1 Formulation of BP identification problem

It is noted that additional unknown sources of BP generation are considered in this study. Along with that, the objective of this paper is to identify the BP sources and quantify the generated BP concentration using several measurements of BP concentration at the end node of each branch pipe, which is a point of natural gas use (client). As most of the gas transmission pipeline network is buried underground, therefore the sensor used for BP concentration measurement is only installed at each client (Abou-Khousa *et al.*, 2015). The presence of an optimization algorithm for BP source identification is developed based on a 1-D model, which has several assumptions (Filali *et al.*, 2016), such as, one-way flow of gas stream, constant velocity of gas flow at each pipe, average mixture of solid particles and gas stream, fixed size/diameter of solid particle, etc., but some additional assumptions should be also taken into consideration. The accuracy of BP source identification is largely restricted because of limited measurement of BP concentration along the pipe, which mainly results from two aspects: (1) lack of reliable measuring device that can be installed underground; (2) the "additional" BP generation from the internal walls is unpredictable, that is, the occurrence of chemical corrosion is highly random and the location is difficult to be identified. Therefore, the gas supply station is assumed in this paper as the main BP generation source, while the junctions stand for additional source, which essentially represent the amount of BP generated along its downstream. Herein, two assumptions are given for the problem formulation of BP identification:

(a) BP source is located in junction only.
(b) Additional BP particle generation occurs in the main pipe only.

According to Figure 1, there is one main BP particle source and several unknown additional sources located at each junction, which are the connection points for every two main pipes and one branch pipe. Let us consider the gas transmission pipeline network as the system. Measurements of BP concentration at each client are the system inputs and estimations of BP concentration at each source are the system outputs. Therefore, the following constrained optimization problem (Aguirre *et al.*, 2007; Cagnina *et al.*, 2008; Hu and Eberhart, 2002; Liu, 2008; Parsopoulos and Vrahatis, 2002) can be formulated with weighted sum of errors (*e.g.* absolute error) as its cost function.

$$\min_{S_1,\, S_2, S_3, \dots,\, S_i} \sum\nolimits_{k=1}^{m} \lambda_k \left| M_k - \widehat{M}_k(S_1,\ S_2, S_3, \dots,\ S_i) \right|, \quad (6)$$

$$\boldsymbol{s.t.} \begin{cases} S_n > 0, & n = 1, 2, 3, \dots, i \\ \lambda_k > 0 \end{cases},$$

where, S_1, S_2, S_3, …, S_i represent the estimation of BP concentration at sources (S_1 is the main source, and S_2, S_3, …, S_i are the additional source). m is the number of clients and BP measurement points. M_k is the measurement of BP concentration at the client k, which is measured by BP concentration sensor located at the end of each branch pipe and it is simulated using the 1-D model presented in the previous section. $\hat{M}_k$ is the estimated value of BP concentration, λ_k is the weighting parameters for each system input, which could be selected as inverse of each measurement of BP concentration at corresponding client. The optimization algorithm for BP source identification is presented as a flowchart in Figure 2.

3.2 Discussion on unique solution of BP optimization problem

Proposition 3.1 *Based on the given assumptions in Section 3.1, the solution of the formulated optimization problem is unique if and only if the number of measurement is equal to the number of unknown BP source.*

The proof is referred to the Appendix A.

4 Simulation studies

In this section, the optimization algorithm for BP source identification is applied to a real gas transmission pipeline network, including 15 pipes, 16 nodes, and 8 junctions. The geometric parameters of this gas pipeline network are practical data from an existing network. The topology of this network is given in Figure 1, as well as its geometric parameters in Table 1. The remaining parts are extensive simulation studies, including BP identification algorithm applied on gas network with perfect measurements, and sensitivity studies on this algorithm. The sensitivity studies

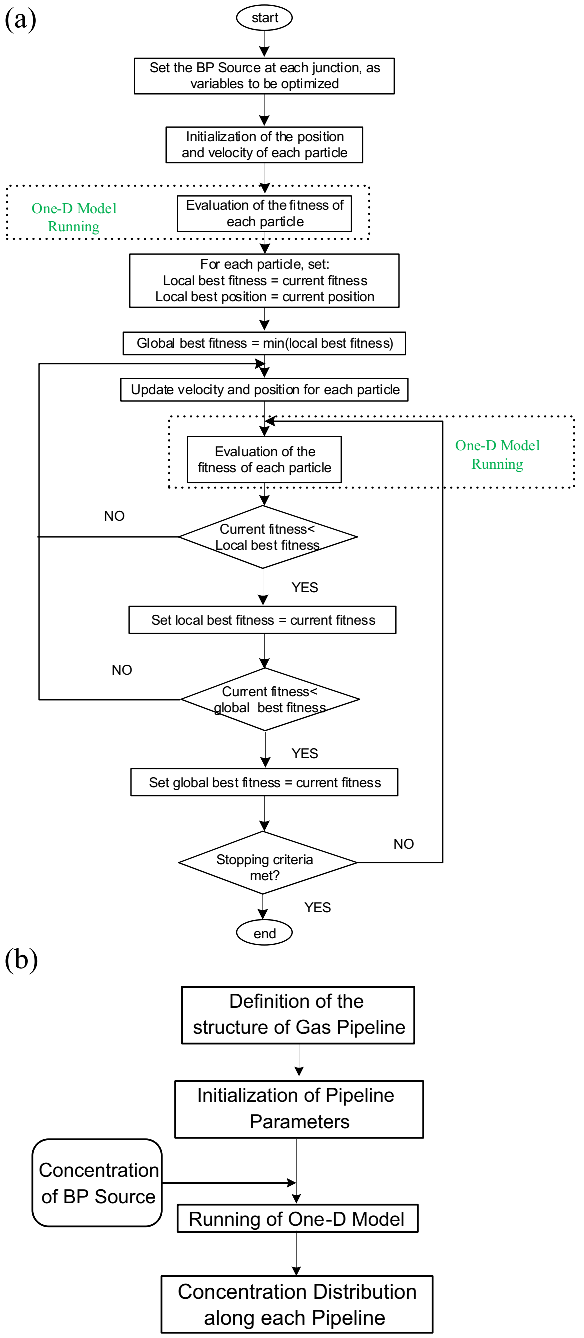


Fig. 2. (a) PSO based BP source optimization algorithm. (b) Flowchart of One-D model running.

are divided into two aspects, including investigations on disturbed measurements and model parameter mismatch. Finally, some discussions are presented.

4.1 Ideal situations

In this section, the optimization algorithm for BP identification is validated on the gas network given in Table 1. It is noted that, initially, the measurements of BP concentration at the end node of each branch pipe (client) are simulated based a sequence of BP sources given as follows.

By sole running of the 1-D model, the measurements of BP concentration at each client could be generated according to the BP concentration at each source given in Table 2. Then these measurements shown in Table 3, will be saved and assumed as known parameters, *i.e.* BP concentration measurements. This is the first step for following simulation studies. The second step is the estimation of BP concentration at each source using the measurements of BP concentration. It is noticeable that the aim of BP optimization problem is the reverse process, where the BP concentration at each source will be estimated by application of the optimization algorithm.

Simulation results of identification for BP concentration at sources are given in Figure 4. In this simulation study, the parameters of PSO are selected as: $\lambda_k = \frac{1}{M_k}$, $n = 300$, $m = 50$, $c_1 = 2$, $c_2 = 2$, where, λ_k is the weighting parameter in equation (6), n is the quantity of particles, m is the maximum number of iteration (termination condition), and c_1, c_2 are the acceleration constants. It is noticeable that the PSO parameters are tuned by trial and error, which can ensure satisfactory performance with acceptable computational load. PSO is a stochastic optimization technique, therefore the algorithm is repeated three times (blue, red

Table 1. Geometric parameters and flow conditions for gas network.

Pipe No.	Pipe length (m)	Pipe diameter (inch)	Mass flow rate, Q (kg/s)	Gas density (kg/m^3)	Start node	End node
P_1	10 000	36	130.092	26.3	S_1	S_2
B_1	3000	10	13.364	25	S_2	M_1
P_2	13 000	36	116.728	23	S_2	S_3
B_2	11 000	24	14.5	26	S_3	M_2
P_3	12 000	36	102.228	25	S_3	S_4
B_3	3000	10	13.364	26.3	S_4	M_3
P_4	3000	36	88.864	25	S_4	S_5
B_4	11 000	24	14.5	23	S_5	M_4
P_5	11 000	36	74.364	26	S_5	S_6
B_5	10 000	24	13.364	25	S_6	M_5
P_6	10 000	36	61	26.3	S_6	S_7
B_6	3000	10	14.5	25	S_7	M_6
P_7	13 000	36	46.5	23	S_7	S_8
B_7	11 000	24	15.5	26	S_8	M_7
B_8	12 000	24	31	25	S_8	M_8

Table 2. Real value of BP concentration at each source.

Source No.	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8
BP concentration (kg/m^3)	9.5	6	7.5	5	4.5	8	5.5	0.5

Table 3. Measurements of BP concentration at each client.

Client No.	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8
BP concentration (kg/m^3)	0.3802	0.1404	0.4831	0.2604	0.1753	1.3014	0.2888	1.3857

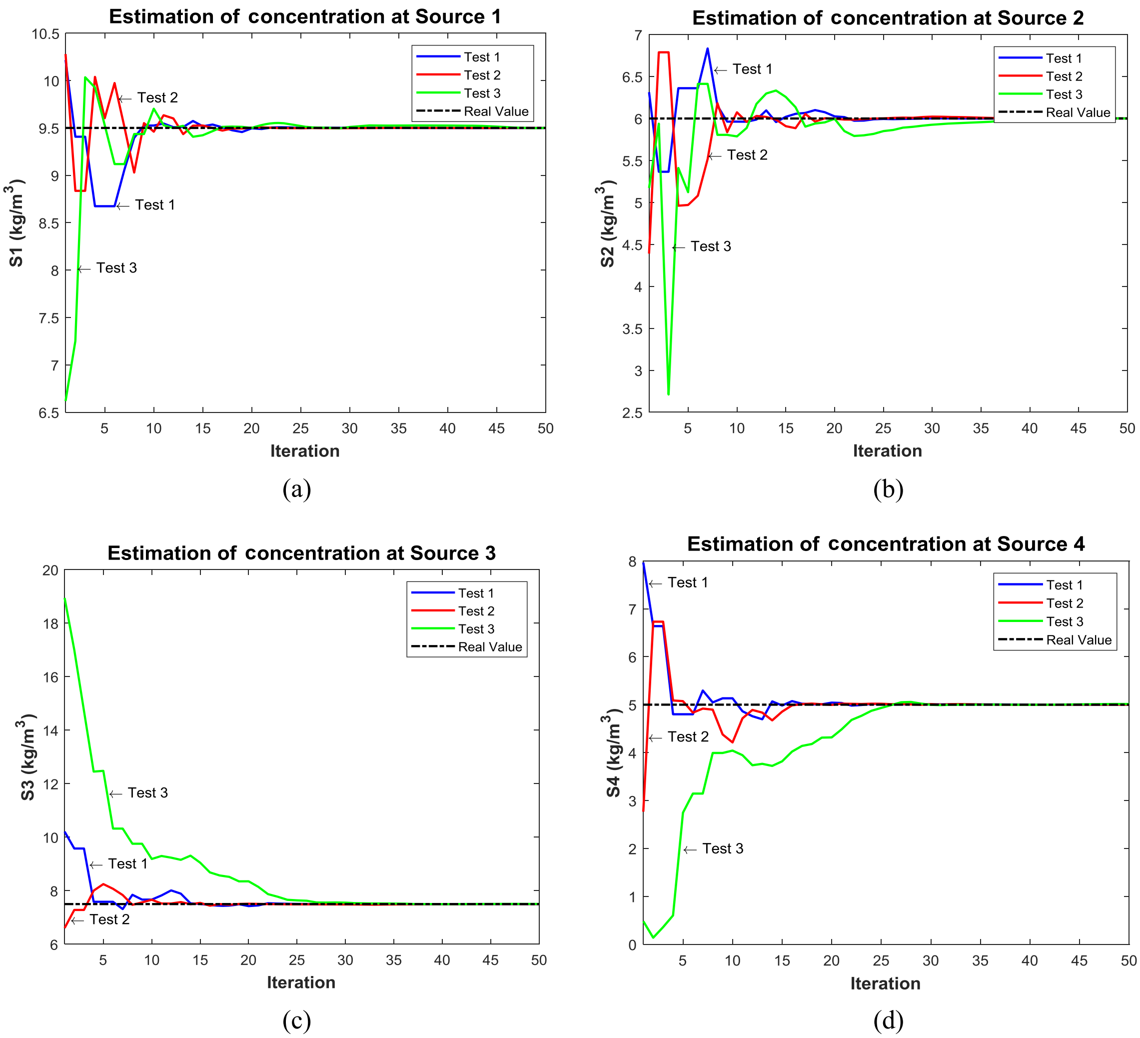


Fig. 4. Estimations of BP concentration at each source, figures (a)–(h) represent sources 1–8.

and green curves in each figure) to show/compare the stability of the optimization results. The dotted line in each figure represents the real value of BP concentration at each source, which is corresponding to Table 3. In addition, the statistic results of each test are summarized in Table 4. The estimation value and absolute error are given for each test and source, and an overall average with the Standard Derivation (SD) are given for all sources. It could be concluded that the optimization algorithm for BP source identification is satisfactory and able to achieve small estimation errors with perfect measurements of BP concentration at clients.

4.2 Sensitivity studies

As stated in Section 4.1, the BP concentration at sources can be well estimated/reproduced by the PSO algorithm when the model is completely known and there are no uncertainties in measurements. However, the efficacy of this approach is still questionable in practice, because all the models are at best only approximations for reality due to various model errors or parametric uncertainties. This problem can be formulated as follows:

$$M_k(\theta) = \widehat{M}_k(\theta, S^*) + \epsilon, \tag{7}$$

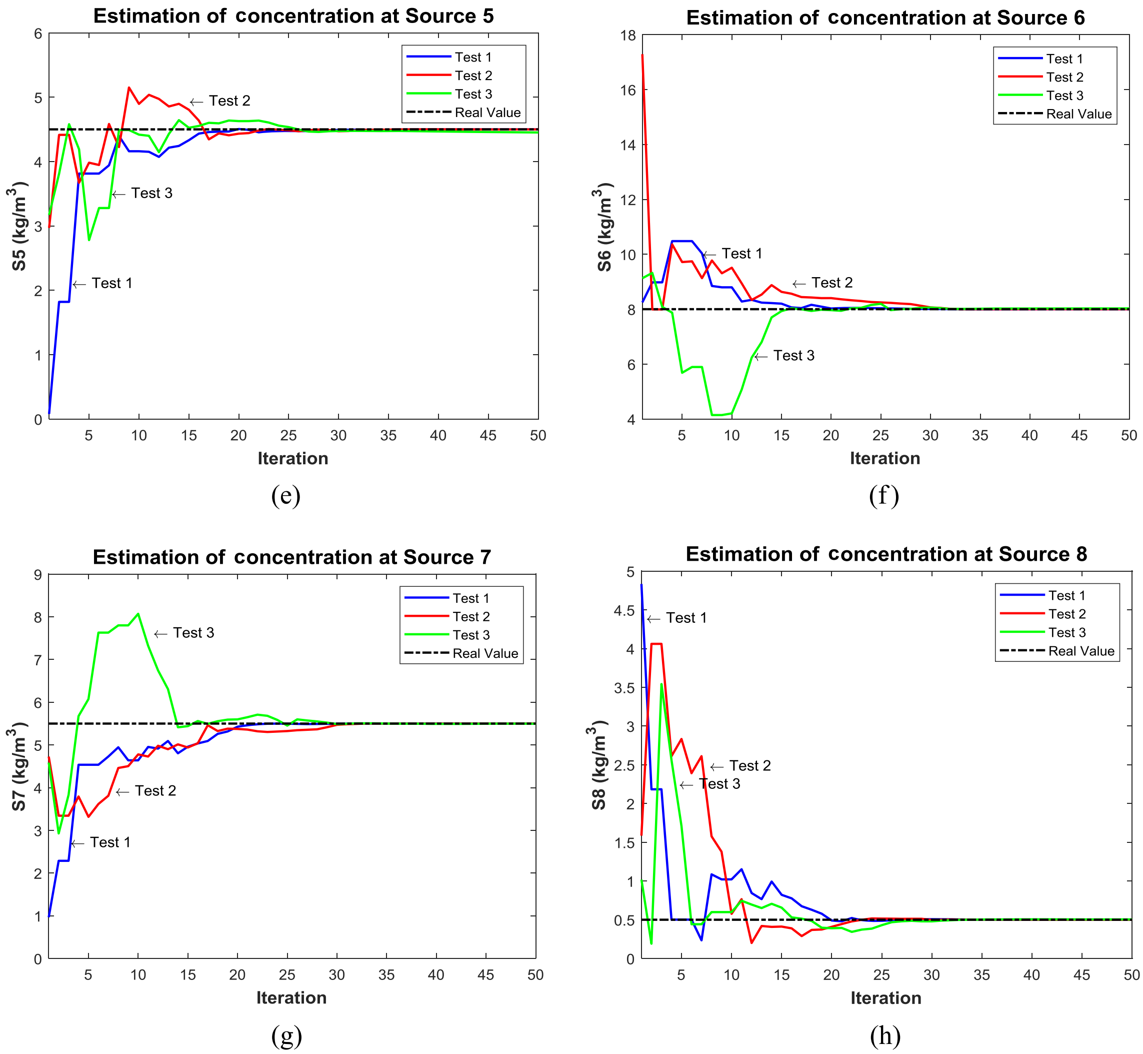


Fig. 4. Continued.

with θ the vector of geometric and flow conditions parameters, ϵ the measurement error, M_k the real measurements, $\widehat{M}_k$ the 1-D model approximation and S^* the vector of BP concentration at sources which are unknown. The aim is to effectively recover S^* *via* PSO algorithm relying on M_k, regardless of the presence of uncertainties in θ and ϵ. A good approach to solve this problem is associated to robust model calibration and inverse problem theory (Tarantola, 1987; Kaipio, 2008).

As a preliminary study, three case studies are simulated in this section. Firstly, the measurement error on M_3 and M_5 are simulated. Secondly, the disturbances in flow measurements are considered. Thirdly, parametric uncertainties are simulated for pipeline roughness. It is noted that each case study is repeated three times with same parameters to prove the algorithm's stability and reliability.

4.2.1 Black Powder measurement uncertainty

In this section, the optimization algorithm for BP source identification is tested under the situations of measurement uncertainty, where M_3 and M_5 are increased by 5% respectively. Basically, ε is regarded as an additive nonzero noise and no variations in θ in this scenario. The tuned parameters for the algorithm are the same with ideal situations. Some figures and statistic data are presented as preliminary results. It is noted that the problem formulation in equation (7) is a deterministic case, which will be generalized in the next stage of experimental validations and tackled by the likelihood approaches (Tarantola, 1987), where measurement errors can be modelled with a probabilistic distribution and confidence intervals will be computed for estimated BP concentration at sources within Bayesian framework.

4.2.1.1 Uncertainty in M_3 measurement

In this case, the BP concentration measurement M_3 is increased by 5%. The performance of identification is shown in Figure 5, and also the corresponding statistic data is presented in Table 5. It can be seen from Figures 5c and 5d, 10% and 5% estimation error for sources 3 and 4

Table 4. Simulation results of optimization algorithm under ideal situations.

BP source	Data set								
	Simulation results						Statistic data		
	Test 1		Test 2		Test 3				
	Estimation	Abs. Error	Estimation	Abs. Error	Estimation	Abs. Error	Real	Avg.	SD
S_1	9.4994	0.0006	9.4996	0.0004	9.5007	0.0007	9.5000	9.4999	0.0006
S_2	6.0004	0.0004	6.0003	0.0003	5.9997	0.0003	6.0000	6.0001	0.0003
S_3	7.5000	0.0000	7.4998	0.0002	7.5036	0.0036	7.5000	7.5011	0.0017
S_4	5.0005	0.0005	5.0001	0.0001	5.0133	0.0133	5.0000	5.0046	0.0061
S_5	4.4994	0.0006	4.4995	0.0005	4.4521	0.0479	4.5000	4.4837	0.0223
S_6	8.0001	0.0001	8.0004	0.0004	8.0283	0.0283	8.0000	8.0096	0.0132
S_7	5.5000	0.0000	5.5000	0.0000	5.4950	0.0050	5.5000	5.4983	0.0024
S_8	0.5000	0.0000	0.5000	0.0000	0.5041	0.0041	0.5000	0.5014	0.0019
Cost function	0.0001		0.0001		0.0037		0.0000	0.0013	0.0017

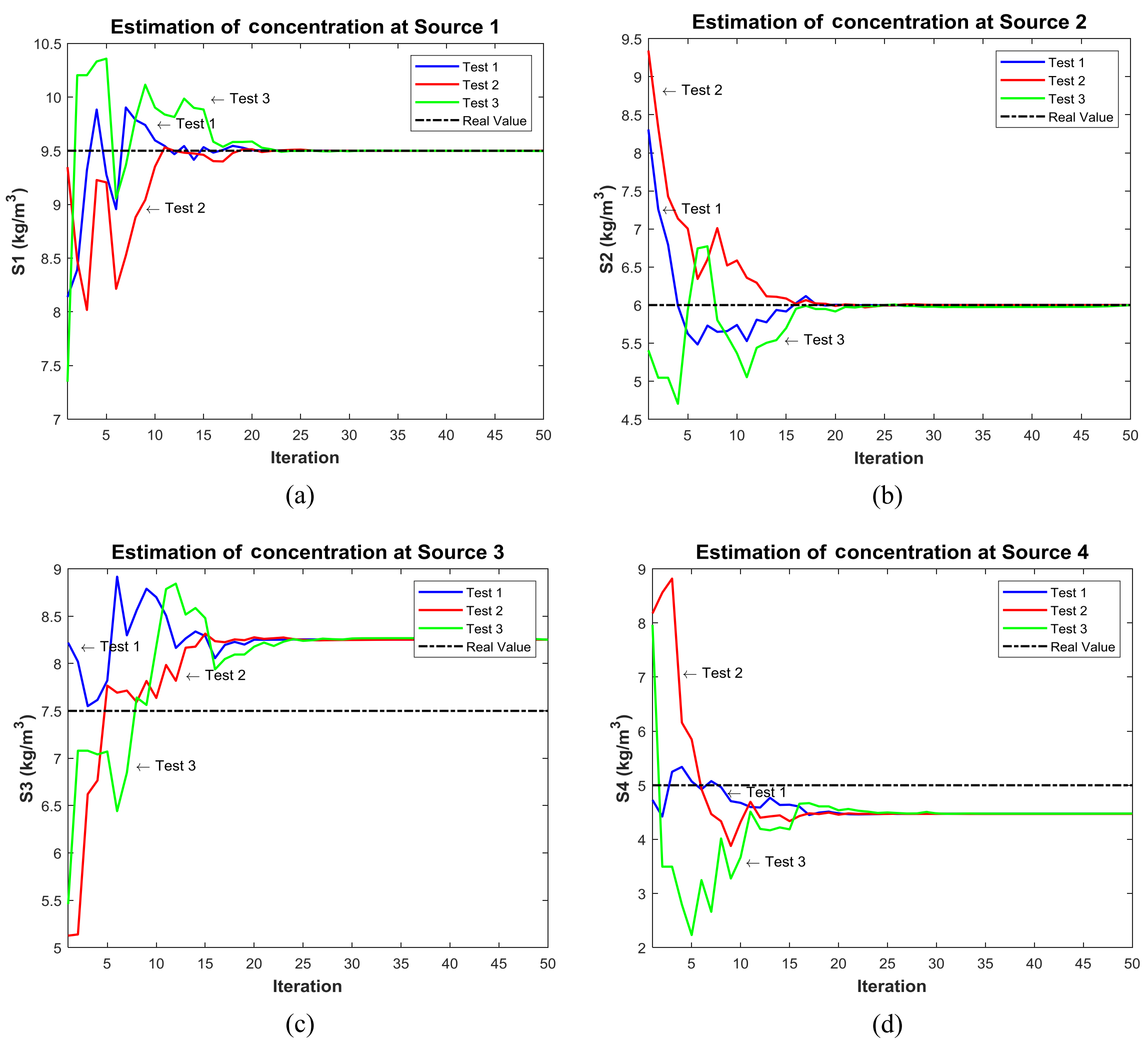
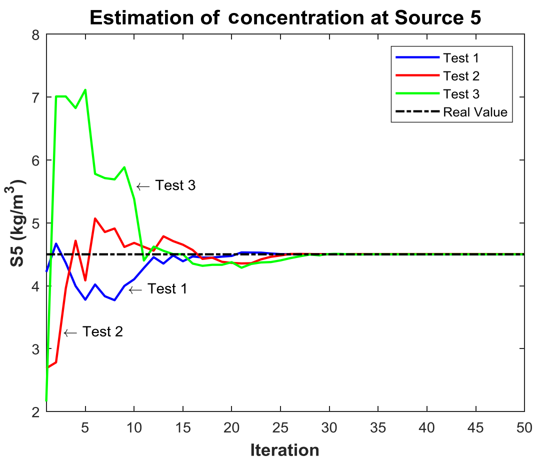
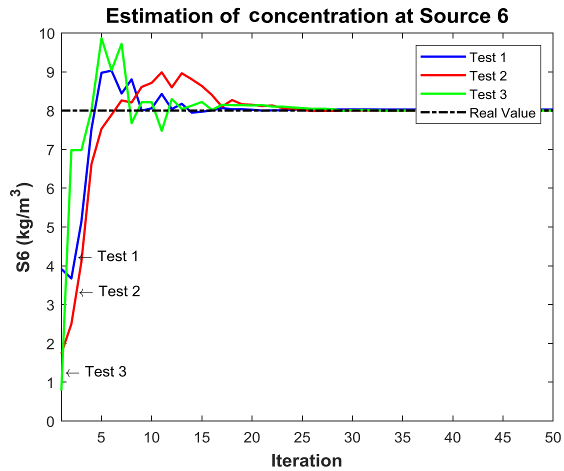


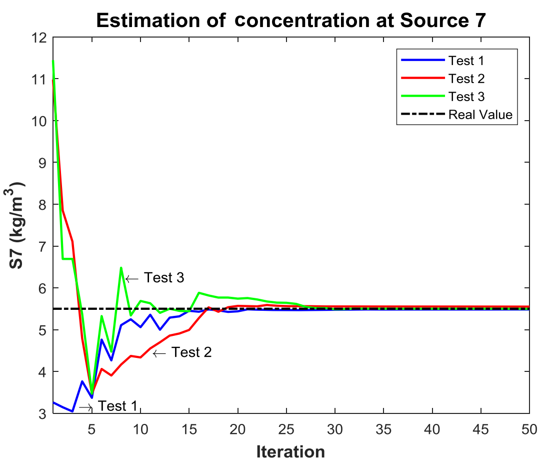
Fig. 5. Estimations of BP concentration at sources for 5% increase in M_3 BP measurements; figures (a)–(h) represent sources 1–8.



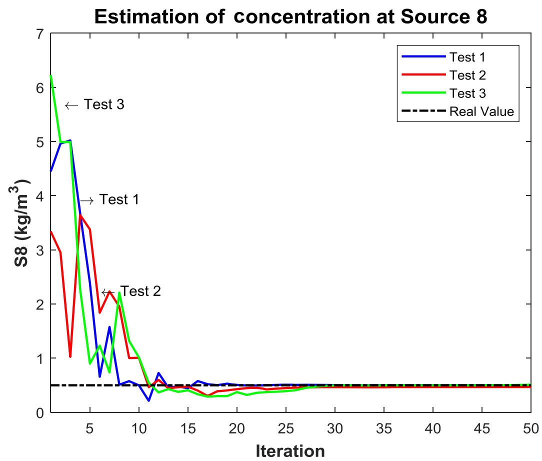
(e)



(f)



(g)



(h)

Fig. 5. Continued.

Table 5. Simulation results of optimization algorithm under situation for 5% increase in M_3.

BP source	Data set								
	Simulation results						Statistic data		
	Test 1		Test 2		Test 3				
	Estimation	Abs. Error	Estimation	Abs. Error	Estimation	Abs. Error	Real	Avg.	SD
S_1	9.4999	0.0001	9.5000	0.0000	9.4963	0.0037	9.5000	9.4987	0.0017
S_2	6.0000	0.0000	6.0000	0.0000	6.0000	0.0000	6.0000	6.0000	0.0000
S_3	8.2524	0.7524	8.2523	0.7523	8.2519	0.7519	7.5000	8.2522	0.0002
S_4	4.4748	0.5252	4.4704	0.5296	4.4768	0.5232	5.0000	4.4740	0.0027
S_5	4.5000	0.0000	4.5038	0.0038	4.5001	0.0001	4.5000	4.5013	0.0017
S_6	8.0266	0.0266	8.0006	0.0006	7.9997	0.0003	8.0000	8.0090	0.0125
S_7	5.4831	0.0169	5.5508	0.0508	5.4971	0.0029	5.5000	5.5103	0.0292
S_8	0.5000	0.0000	0.4678	0.0322	0.5100	0.0100	0.5000	0.4926	0.0180
Cost function	0.0012		0.0030		0.0016		0.0000	0.0019	0.0008

Table 6. Simulation results of optimization algorithm under situation for 5% increase in M_5.

BP source	Data set								
	Simulation results						Statistic data		
	Test 1		Test 2		Test 3				
	Estimation	Abs. Error	Estimation	Abs. Error	Estimation	Abs. Error	Real	Avg.	SD
S_1	9.4961	0.0039	9.5000	0.0000	9.5000	0.0000	9.5000	9.4987	0.0018
S_2	6.0037	0.0037	5.9952	0.0048	6.0000	0.0000	6.0000	5.9996	0.0035
S_3	7.4992	0.0008	7.5030	0.0030	7.5001	0.0001	7.5000	7.5007	0.0016
S_4	4.9988	0.0012	5.0000	0.0000	4.9999	0.0001	5.0000	4.9996	0.0006
S_5	5.3850	0.8850	5.3828	0.8828	5.3829	0.8829	4.5000	5.3836	0.0010
S_6	7.2908	0.7092	7.3189	0.6811	7.3133	0.6867	8.0000	7.3077	0.0121
S_7	5.5141	0.0141	5.4965	0.0035	5.4778	0.0222	5.5000	5.4961	0.0148
S_8	0.5030	0.0030	0.5002	0.0002	0.5140	0.0140	0.5000	0.5057	0.0060
Cost function	0.0019		0.0007		0.0012		0.0000	0.0012	0.0005

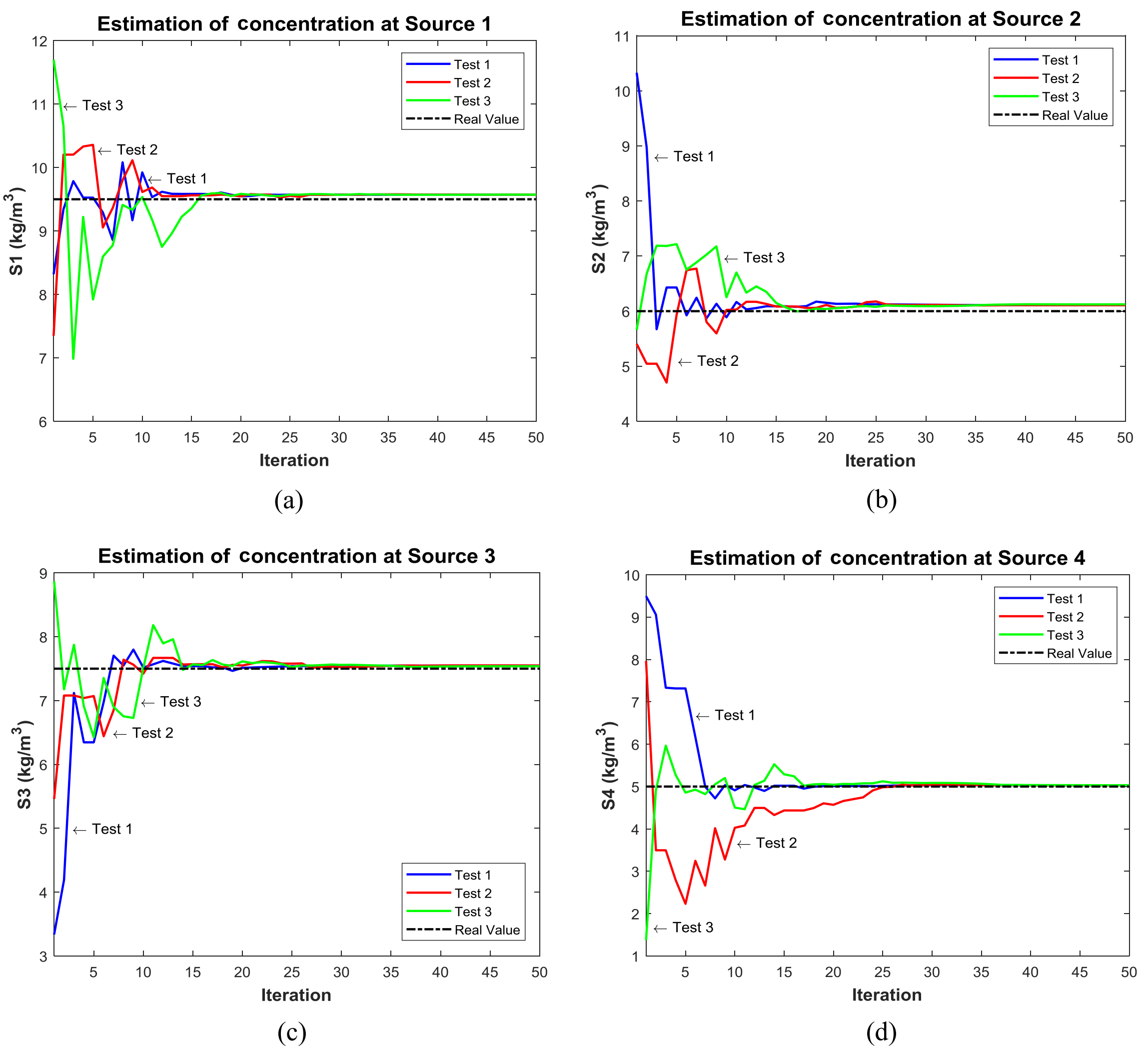
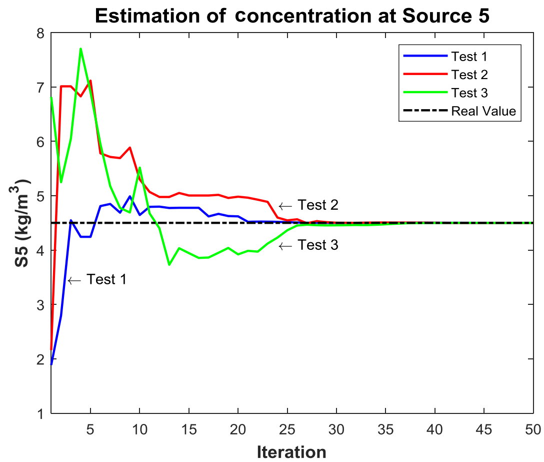


Fig. 6. Estimations of BP concentration at sources for 10% increase in Q_3, figures (a)–(h) represent sources 1–8.



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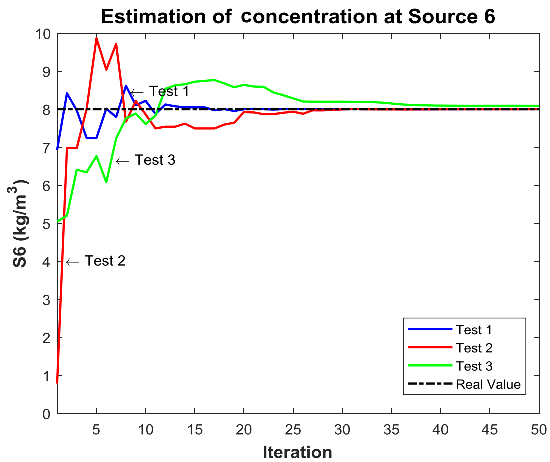

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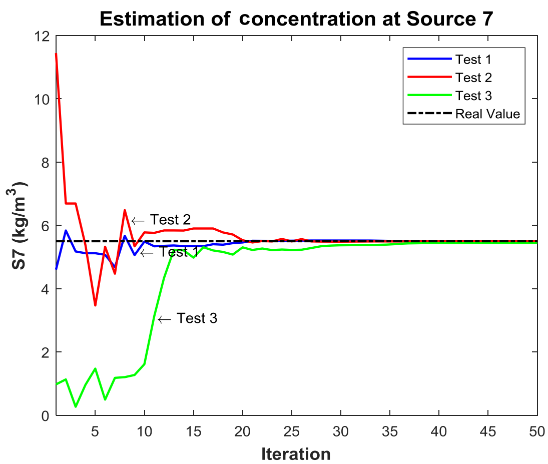
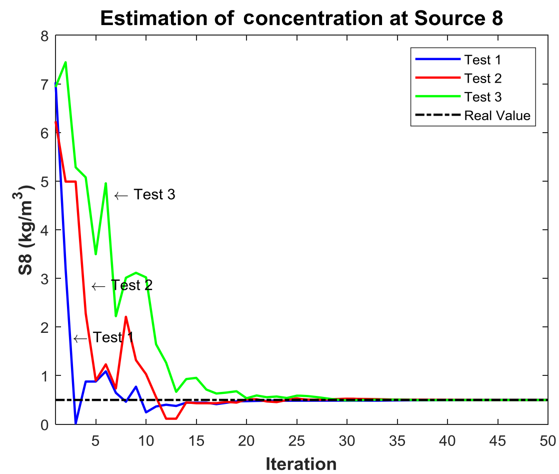


(g)



(h)

Fig. 6. Continued.

Table 7. Simulation results of optimization algorithm under situation for 10% increase in Q_3.

BP source	Data set								
	Simulation results						Statistic data		
	Test 1		Test 2		Test 3				
	Estimation	Abs. Error	Estimation	Abs. Error	Estimation	Abs. Error	Real	Avg.	SD
S_1	9.5730	0.0730	9.5730	0.0730	9.5728	0.0728	9.5000	9.5730	0.0001
S_2	6.1084	0.1084	6.1086	0.1086	6.1237	0.1237	6.0000	6.1136	0.0072
S_3	7.5472	0.0472	7.5485	0.0485	7.5379	0.0379	7.5000	7.5445	0.0047
S_4	5.0310	0.0310	5.0304	0.0304	5.0310	0.0310	5.0000	5.0308	0.0003
S_5	4.5004	0.0004	4.4997	0.0003	4.5003	0.0003	4.5000	4.5001	0.0003
S_6	8.0002	0.0002	8.0010	0.0010	8.0895	0.0895	8.0000	8.0302	0.0419
S_7	5.5001	0.0001	5.4993	0.0007	5.4441	0.0559	5.5000	5.4812	0.0262
S_8	0.5000	0.0000	0.5003	0.0003	0.4994	0.0006	0.5000	0.4999	0.0004
Cost function	0.0001		0.0002		0.0055		0.0000	0.0019	0.0025

Table 8. Simulation results of optimization algorithm under situation for 5% increase in Q_5.

BP source	Data set								
	Simulation results						Statistic data		
	Test 1		Test 2		Test 3				
	Estimation	Abs. Error	Estimation	Abs. Error	Estimation	Abs. Error	Real	Avg.	SD
S_1	9.5364	0.0364	9.5352	0.0352	9.5481	0.0481	9.5000	9.5399	0.0058
S_2	6.0551	0.0551	6.0547	0.0547	6.0356	0.0356	6.0000	6.0485	0.0091
S_3	7.5437	0.0437	7.5457	0.0457	7.4902	0.0098	7.5000	7.5265	0.0257
S_4	5.0098	0.0098	5.0114	0.0114	5.0440	0.0440	5.0000	5.0217	0.0158
S_5	4.4390	0.0610	4.4366	0.0634	4.4514	0.0486	4.5000	4.4424	0.0065
S_6	8.0688	0.0688	8.0671	0.0671	8.0619	0.0619	8.0000	8.0659	0.0029
S_7	5.4989	0.0011	5.4969	0.0031	5.6637	0.1637	5.5000	5.5532	0.0782
S_8	0.5009	0.0009	0.5027	0.0027	0.3986	0.1014	0.5000	0.4674	0.0487
Cost function	0.0003		0.0006		0.0157		0.0000	0.0055	0.0072

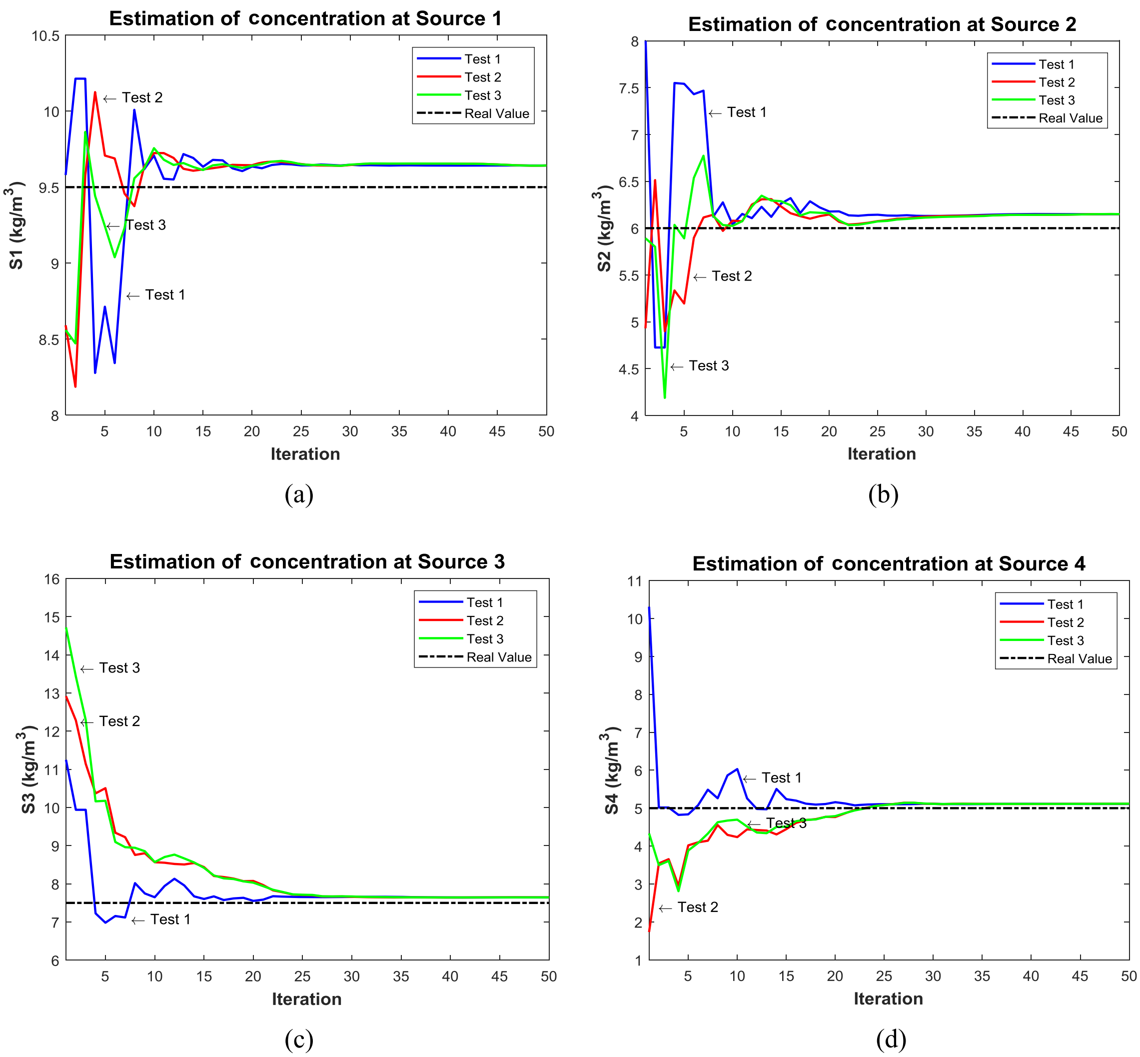


Fig. 7. Estimations of BP concentration at sources for 5% increase in roughness, figures (a)–(h) represent sources 1–8.

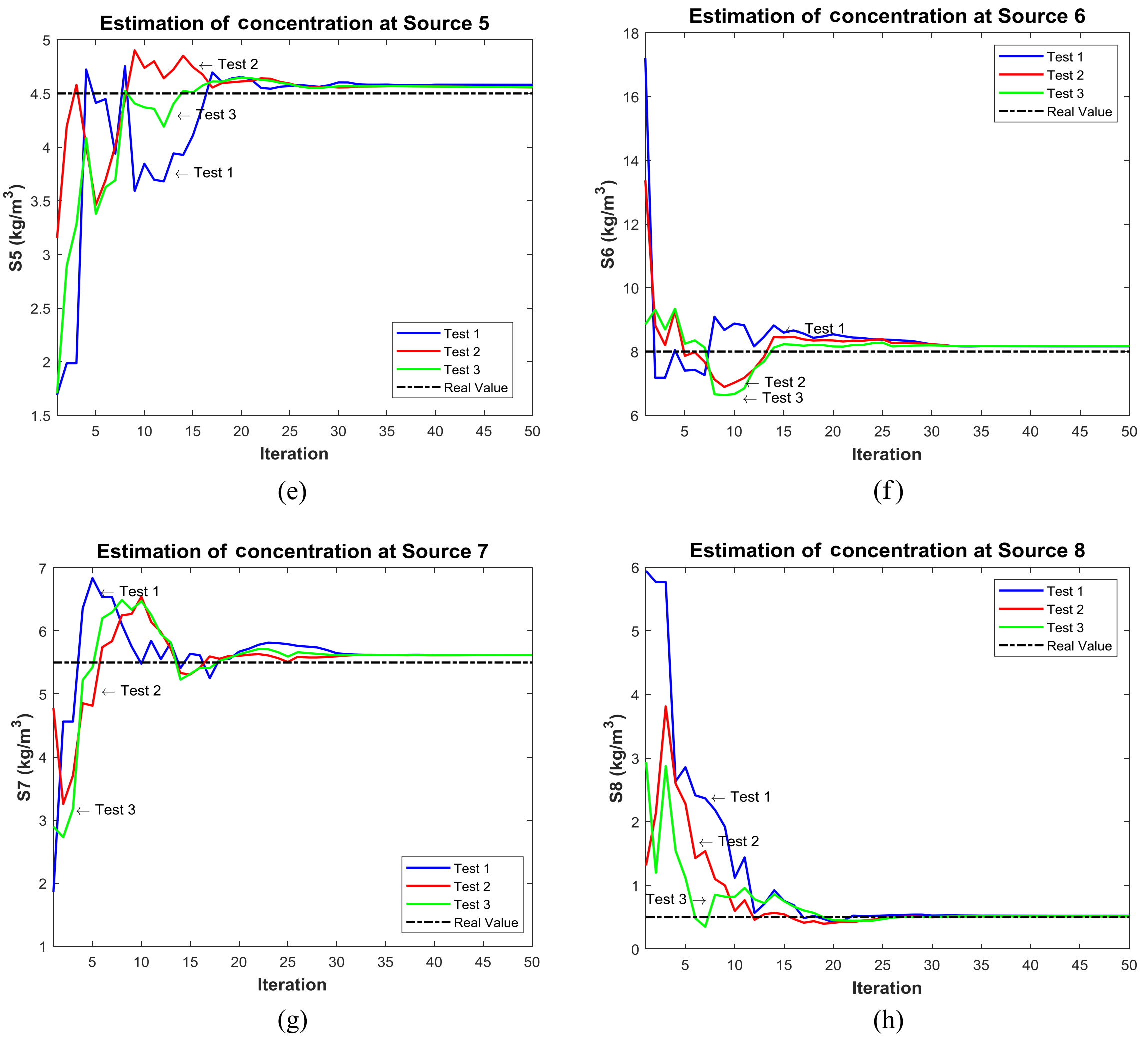


Fig. 7. Continued.

respectively, which are expected and acceptable. Although the inaccurate measurement occurring at M_3 affects the BP concentration estimation at sources 3 and 4, and it has negligible influence on the BP concentration estimation at sources 5, 6, and the downward sources.

4.2.1.2 Uncertainty in M_5 measurement

In this case study, M_5 is increased by 5% and the performance of the optimization algorithm is presented in Table 6. It is noted that the estimation errors of sources 5 and 6 are 15% and 10% respectively, which are high relatively compared with their downward sources. The estimation error of sources 7 and 8 could be negligible.

4.2.2 Mass flow rate measurement uncertainty

Similarly, variations in θ are simulated in this section, where the mass flow rate in pipe 3 (Q_3) and pipe 5 (Q_5) are increased by 10% and 5% respectively. The tuned parameters for PSO are same with the ideal situations. One objective of this paper is to study the robustness of the model fidelity to measurement data given parametric uncertainties. Although these simulation tests are not representative in practice where noise/uncertainties always exist in a stochastic way, they can provide some preliminary results at this stage.

4.2.2.1 Uncertainty in Q_3 measurement

In this case study, the mass flow rate measurement of Q_3 is increased by 10%. The simulation results are shown in Figure 6, along with its statistic data in Table 7. It can be seen in Figure 6, the variation of flow rate Q_3 has a very small influence on the optimization, which proves the robustness of the optimization algorithm under uncertainty.

4.2.2.2 Uncertainty in Q_5 measurement

In this case study, the mass flow rate measurement of Q_5 is increased by 5%. The simulation results are shown in Table 8. The estimation error is less than 2% for each source, which is acceptance and negligible for this work.

Table 9. Simulation results of optimization algorithm under situation for 5% increase in roughness.

BP source	Data set								
	Simulation results						Statistic data		
	Test 1		Test 2		Test 3				
	Estimation	Abs. Error	Estimation	Abs. Error	Estimation	Abs. Error	Real	Avg.	SD
S_1	9.6425	0.1425	9.6367	0.1367	9.6235	0.1235	9.5000	9.6342	0.0097
S_2	6.1501	0.1501	6.1489	0.1489	6.1427	0.1427	6.0000	6.1472	0.0040
S_3	7.6425	0.1425	7.6349	0.1349	7.6429	0.1429	7.5000	7.6401	0.0045
S_4	5.1102	0.1102	5.1045	0.1045	5.1049	0.1049	5.0000	5.1065	0.0032
S_5	4.5810	0.0810	4.5727	0.0727	4.5829	0.0829	4.5000	4.5789	0.0054
S_6	8.1640	0.1640	8.1594	0.1594	8.1587	0.1587	8.0000	8.1607	0.0029
S_7	5.6188	0.1188	5.6037	0.1037	5.6134	0.1134	5.5000	5.6120	0.0077
S_8	0.5109	0.0109	0.5107	0.0107	0.5106	0.0106	0.5000	0.5107	1.5e-4
Cost function	0.0023		0.0046		0.0032		0.0000		

4.2.3 Deposition rate uncertainty

In this case study, the pipeline roughness is increased by 5%. The parameter for the algorithm is same with the ideal case and some simulation results are shown above:

It can be seen in Figure 7 that the estimation of BP concentration for each client is always higher than the expected value, and the estimation error is shown in Table 9. This is reasonable because the increase of roughness will result in more BP deposition, in other words, more BP should be generated in order to achieve the same measured BP concentration as expected. However, the average estimation error is nearly 2%, which is still acceptable in the practical situation.

5 Conclusion

In this paper, the problem of BP source identification is studied by applying a PSO-based optimization algorithm, which is developed upon a 1-D model of BP transport and deposition. The 1-D model is a simplified approach for modelling the dynamics of BP particles in gas transmission pipeline network. A schematic of tree-shaped gas network is proposed, which is generalized with a set of connection rules. Through some preliminary simulation studies, the PSO-based algorithm is validated to be a useful technique for BP source identification. At this stage, the model errors and uncertainties are assumed deterministic though they are not representative in practice. The main purpose of this paper is to discuss the application of PSO techniques on BP source identification. More work will be done together with the experimental studies in the next stage, including (1) analysis of likelihood approach which has specified probabilistic distribution to model error; (2) improvement of the 1-D model by considering pickup case and various particle sizes.

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Appendix A

Proof for the Proposition 3.1

1) Sufficiency: To prove the uniqueness of the optimal solution, let us consider the general structure of tree-shaped gas pipeline network, as shown in Figure 3. The network consists of N pipes, $N+1$ nodes and $(N-1)/2$ junctions.

According to the 1-D model, the concentration at the end node of each branch pipe is given as a function of BP sources, where we have $\frac{(N-1)}{2}+1$ unknown BP source to be identified. The following equations can be easily found if we split the influence of each source on each measurement.

$$M_1 = f(S_1), \tag{A1.a}$$

$$M_2 = f(S_1, S_2) = f_{21}(S_1) + f_{22}(S_2), \tag{A1.b}$$

$$M_3 = f(S_1, S_2, S_3) = f_{31}(S_1) + f_{32}(S_2) + f_{33}(S_3), \quad \vdots \tag{A1.c}$$

The compact form of above equations is

$$M_k = \sum_{i=1}^{\frac{(N-1)}{2}+1} f_{ki}(S_i). \tag{A2}$$

It is noted that the functions involved must be invertible, which are determined by the physical properties of the gas transmission pipelines. Although there is not explicit mathematical function describing the mapping between S and M, this function must be invertible at a particular time instant because the physical properties of pipeline do not change. Let us start with the first source S_1 in equation (A1.a), the concentration could be determined by the first measurement M_1 only. Based on equation (A1.b), the second measurement M_2 is represented as a function of (S_1) and (S_2). Then, f_{21} (S_1) can be obtained according to S_1, which has been calculated from equation (A1.a). Therefore, $f_{22}(S_2)$, the remaining term of M_2, could be used to

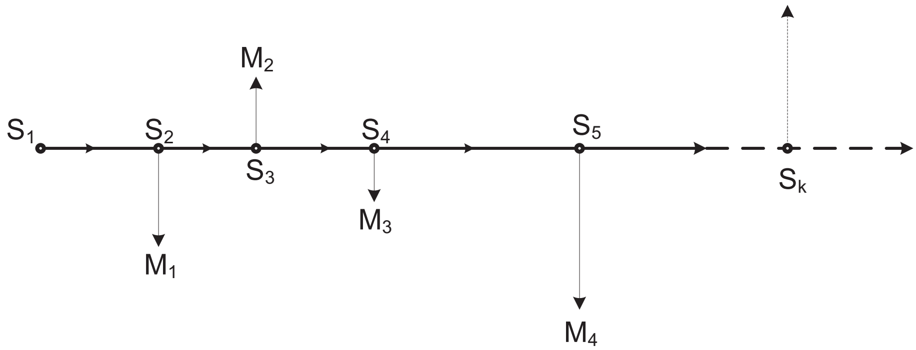

Fig. 3. Generalized tree-shaped gas transmission pipeline network with additional BP source.

determine the concentration at source S_2. Consequently, the remaining sources S_k can be determined step by step.

2) Necessity: If the number of client node measurements is less than the number of unknown BP source, for example, M_j $(1 < j < \frac{(N-1)}{2} + 1)$ is not available, *i.e.* is not measured due to fault.

Let us consider equation M_{j+1}:

$$M_{j+1} = \sum_{i=1}^{j-1} f_{j+1,\,i}(S_i) + f_{j+1,\,j}\big(S_j\big) + f_{j+1,\,j+1}\big(S_{j+1}\big), \quad \text{(A3)}$$

where, $\sum_{i=1}^{j-1} f_{j+1,i}(S_i)$ represents the influence of source S_1 to S_{j-1} on M_{j+1}. $f_{j+1,j}(S_j)$ and $f_{j+1,j+1}(S_{j+1})$ represent the influence of S_j and S_{j+1} on M_{j+1} respectively. Therefore, S_j is a preliminary condition to identify S_{j+1}. However, S_j cannot be identified because M_j is not available. In other word, unique solution of S_j and S_{j+1} cannot be achieved in this situation.