Assessment of Black Powder Concentrations in Natural Gas Pipeline Networks

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This work was supported by the Gas Processing and Materials Science Research Center (GRC), Khalifa University, Abu Dhabi, United Arab Emirates.

ABSTRACT Natural gas transmission pipeline networks are facing serious issues related to the solid particles deposition that is called black powder (BP). The creation of BP inside natural gas pipeline is not completely understood, but it mainly results from the pipelines inner walls corrosion, which is a complex chemical reaction between the natural gas and pipelines. Moreover, the exact BP generation time, amount, and location are still vague. This work aims to reduce the effect of BP by estimating BP concentrations in natural gas networks. This will significantly help natural gas pipeline networks operators to plan more effective maintenance schedules. This work takes into account the industrial need for simple, fast, and accurate techniques for estimating BP concentration in natural gas pipeline networks. The proposed BP estimation technique is based on a lookup table (LT) which is constructed from a one-dimensional model of BP deposition and transport. This technique eliminates the need for extensive computational efforts and long estimation times that are necessary for other optimization-based BP estimation techniques. The proposed LT-based BP estimation technique is validated and compared to other BP estimation techniques using simulation studies. The results of the proposed BP estimation technique show that it is promising and has potentials for application in existing and future natural gas networks.

INDEX TERMS Black powder (BP), lookup table (LT), natural gas network, optimization techniques.

I. INTRODUCTION

Natural gas is a critical industry, and ensuring safe and efficient operation is a challenging task. Natural gas pipeline networks are sophisticated and spread over large geographical areas. One of the most important phenomena that affect the natural gas industry is black powder (BP) [1], [2]. BP consists of tiny black particles and can be found in both gas and liquid natural gas pipelines. It is created from the interaction of chemical elements such as metals, water, and hydrocarbons inside the natural gas pipeline. BP composition has high gravity and adsorption properties. The source of BP comes from the gas source itself or pipeline walls due to corrosion [3]–[5]. Figure 1 shows BP in a natural gas pipeline [6]. BP has negative impacts on natural gas pipelines. The first impact is gas quality degrade. The gas will not be pure as it will include harmful particles. The second impact is operational costs increase. The pressure inside the natural gas pipelines will decrease, and this will lead to higher resistance for compressors. The third impact of BP is that it affects the natural gas network monitoring equipment such as flow meters, and this results in misleading network information [7], [8].

Oil and gas companies are adopting two ways to fight BP which are protection and elimination. BP prevention is achieved by coating the natural gas pipeline inner walls with BP prevention films. Moreover, decreasing the water levels inside the natural gas pipelines also protects from corrosion. BP protection techniques are efficient, but it is hard to apply them for pipes under operation [9], [10]. On the other hand, BP elimination is achieved by mechanical or/and chemical cleaning. Mechanical cleaning includes internal walls scrapers and filters while chemical cleaning includes injecting cleaning components inside the pipeline. BP elimination is a practical way to reduce the BP negative effects, but repeated cleaning would damage the pipelines and increase the repairing costs [11], [12].
BP mitigation solutions do not handle BP formation location, and some of them may be dangerous for the environment, chemical cleaning for instance. The exact amount and location of BP source is unclear, and the major reason is the vague information related to BP creation. In addition, BP generation is time-varying, and it is influenced by various characteristics and conditions [13]–[15].

A. MOTIVATIONS
The motivation of this work came from an existing issue in gas distribution networks. Oil and gas companies are facing serious problems related to BP with limited solutions in the industry practice and market. The main objective is to detect and monitor the movement of the BP in the gas pipelines. The first step was to invent a sensor that can detect BP in real-time [16], [17]. The second step is to propose an algorithm for higher level monitoring which uses the BP measurements to provide a clear picture of the natural gas network. Initially, advanced and powerful approaches based on optimization were suggested in Ref. [18] and Ref. [19], yet these approaches were not practical for the oil and gas companies. These approaches require huge calculations efforts and complex procedures for testing and implementations. Thus, the need for easier and faster alternative solutions rose, and a relatively simple and implementable approach that is based on lookup tables (LTs) is proposed in this paper.

LTs are veteran methods to search for data. They are fast ways to retrieve information when the data is very large and especially for hardware implementations. LTs are used in many applications such as remote sensing [20], microgrids [21], computer science [22], electric vehicles [23], power electronics [24], and image processing [25].

Practical applications are not ideal, and there will always be a mismatch between actual and estimated quantities. Numerical models and measurements devices have errors and tolerances which affect the accuracy of the estimation method, and this is an important factor that should be considered in any study. Sensors drifting and noise are examples of uncertainties which affect BP concentrations measurements.

B. CONTRIBUTIONS
The main goal of this paper is to estimate the BP sources concentrations in natural gas pipeline networks precisely and practically. This paper serves as an alternative way to the techniques presented in Ref. [18] and Ref. [19]. It also expands the previous studies by including some uncovered topics like the estimation time and the uncertainty in the natural gas pipeline network parameters and BP concentrations measurements.

The major contributions of this article are:

- Practical solution for the natural gas industry due to the reduced BP estimation calculation efforts and time.
- A simplified yet accurate method for BP estimation.
- The proposed LT estimation technique is validated on a larger network with realistic parameters.
- The effects of uncertainties in BP measurements and network parameters are investigated.

The innovation of this paper comes for its simplicity and practicality to help in estimating BP concentrations in natural gas networks. Various approaches are customized to fit with the proposed BP estimation strategy. The BP deposition model that is adopted in this paper is modified to include multiple BP sources. The proposed LT method including LT construction and BP concentrations retrieve is unique.

C. ORGANIZATION
This article is organized as follows. Section I contains introduction and background related to BP formation, effects, and treatment. It also contains the motivations and contributions of this paper. Section II briefs the structure of the natural gas network under study and the BP deposition models. In Section III, the proposed LT method is explained and developed. In Section IV, the results and discussions on the proposed BP estimation method are presented. Finally, the key findings of the article as well as possible future improvements and research directions are provided in Section V.

II. NATURAL GAS NETWORK AND BP DEPOSITION MODELS
In this section, the structure of natural gas network is introduced, and the one-dimensional models for BP transport and deposition in the natural gas network are explained.

A. NATURAL GAS PIPELINE NETWORK
Natural gas pipeline networks are designed to transmit natural gas form the producing point to the consuming point which can be located in very long distances. They have very sophisticated structure that is challenging for conducting advances studies and analyses. Therefore, researchers developed unpretentious ways to make natural gas networks studies feasible. One of the common ways is to represent the network as a simplified structure as shown in Figure 2.
The network has single gas flow direction and fixed BP sources and measurements location points and defined simplification assumptions [19]. The parameters of this network are summarized in Table 1. The five pipes of the natural gas pipeline network have a diameter of 0.5m and roughness of 4.75µm.

### B. ORIGINAL BP DEPOSITION MODEL

BP deposition model [26] is a model that emulates the movement of BP particles in the natural gas pipeline network. The model considers the pipe parameters such as pipe diameter, pipe roughness, gas flow rate, BP particles size, etc. The main reason for selecting this model is the possibility of estimating BP transport for long natural gas networks. This may not be feasible with the (2/3-Dimensional models) computational fluid dynamics (CFD) simulations [27], [28].

In the original one-dimensional model, the flow of gas is blended with BP particles, and the motion of each particle is modelled according to steady scalar advection/reaction equation analytical solutions. Dusty gas assumptions are also considered. The governing equation for gas stream mixed with solid particles is given as the following one-dimensional advection diffusion reaction equation [26]:

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

where \( C \) represents the concentration of the particle in the gas flow, \( U \) represents the average velocity of gas flow inside the pipeline, \( D_{diff} \) represents the diffusion coefficient, and \( S \) describes the solid particles deposition generation or pickup. The axial diffusion term \( D_{diff} \frac{\partial^2 C}{\partial x^2} \) can be ignored by considering the turbulent flow because the advection term \( U \frac{\partial C}{\partial x} \) is more dominant as per the following condition:

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

the steady state solution (1) can be written as:

$$U \frac{\partial C}{\partial x} = -\beta_{dep} C + \delta_{gen}$$

where \( \beta_{dep} \) represents the rate of deposition. \( \delta_{gen} \) is a known factor that represents the rate of the BP production inside the pipe. Figure 3 shows the BP distribution for pipe-1 under different initial BP sources concentrations. The initial point is the BP source, and the final point is BP measurement.

### C. MODIFIED BP DEPOSITION MODEL

The original BP model considers a single BP source, but it is modified in this paper to consider multiple BP sources. This is achieved by implementing the same model several times in subnetworks to get multiple sources. Each subnetwork is independent from the other. In other words, the model is evaluated for each subnetwork, and the BP...
concentrations from all subnetworks are added to get the final BP concentration which is the resultant from all different BP sources. In this case, different BP sources locations can be considered. Figure 4 shows the major variations between the original model [26] and the model adopted in the paper.

III. PROPOSED LOOKUP TABLE METHOD

The main objective of this work is to estimate BP sources concentration in natural gas network. This assists operators in making beneficial decisions related to BP removal. However, BP sources concentrations are unknown in reality. What is available is the BP measurements information that is obtained from BP measurements devices installed in clients side. The prime idea of this work is to utilize the BP model to get a set of BP measurements form different BP sources concentration (known values) and then reverse the operation and retrieve BP sources concentrations from BP measurements. The concept of the proposed BP estimation technique is shown in Figure 5, and the flow diagram of the proposed LT-based BP estimation approach is shown in Figure 6.

The presence of the LT algorithm for BP estimation is developed based on the one-dimensional model. In this study, the system is the natural gas pipeline network, the system inputs are the measurements of BP concentrations, and the system outputs are the estimations of BP concentrations at each source. The proposed LT method is valid for any network size. For the sake of illustration, a small five-pipes network is considered. The proposed LT approach is performed using two steps or algorithms which are LT construction and BP sources concentrations retrieve.

A. LOOKUP TABLE CONSTRUCTION

A LT which considers the range [1,10] for $S_1$ and [0,10] for both $S_2$ and $S_3$ with a step of 1 is generated by inserting the source concentrations ($S_1$, $S_2$, and $S_3$) to the one-dimensional model and record the resultant measurements ($M_1$, $M_2$, and $M_3$). The range is selected based on approximate knowledge from BP cleaning process in natural gas pipeline sites [5]. The first BP source $S_1$ range starts with 1 because the BP model must have a non-zero initial start BP concentration. All BP concentrations in this paper are in Kg/m$^3$. The LT has size 1210 by 6 in this case, and only part of it is summarized in Table 2.

The first algorithm which constructs the LT is concisely given in Algorithm 1. It uses the BP model to generate the LT for $n$ BP sources and $k$ pipes.

### Table 2. Lookup table structure.

| $M_1$  | $M_2$  | $M_3$  | $S_1$ | $S_2$ | $S_3$ |
|--------|--------|--------|-------|-------|-------|
| 0.0844 | 0.00714| 0.0166 | 1 0  0|       |       |
| 0.1688 | 0.01429| 0.0332 | 2 0  0|       |       |
| ...    | ...    | ...    | ...   | ...   | ...   |
| ...    | ...    | ...    | ...   | ...   | ...   |
| 0.7620 | 0.3060 | 3.0029 | 9 10 10|       |       |
| 0.8470 | 0.3133 | 3.0196 | 10 10 10|      |       |

![Figure 6](image-url) **Figure 6.** Flow diagram of the proposed black powder concentrations estimation method.
Algorithm 1 LT Construction Algorithm

1 function Build_LT;
   Input : BP sources concentrations $S_1, S_2, \ldots, S_n$,
   BP_Model, and Pipe length for each pipe $k$
   Output: $LT$
2   for $i = 1$ to $n$ do
3       if ($S_i == 0$) then
4           $M_{S_i} = 0$ ;
5       else
6           $Result_{S_i} = BP_{Model}(S_i)$;
7           for $j = 1$ to $k$ do
8               $M_{S_i}(j) = [Result_{S_i}(Pipe\_Length_j)]$;
9           end
10          $M_{S_i} = sum(M_{S_i})$;
11       end
12   end
13 return $LT$;

Algorithm 2 Find_S Algorithm

1 function Find_S;
   Input : BP measurements $M_1, M_2, \ldots, M_n$, and $LT$
   Output: Estimated BP sources $\hat{S}_1, \hat{S}_2, \hat{S}_3, \ldots, \hat{S}_n$
2   for $i = 1$ to $n$ do
3       $Result_{\hat{S}_i} = interp(LT(i-1), LT\_Range, M_i)$;
4   end
5 return $\hat{S}$;

B. BP SOURCES CONCENTRATIONS RETRIEVE

The LT is used to find the BP sources concentrations using a user defined function named $Find\_S(M_1, M_2, M_3, LT)$. This function needs four inputs which are the BP measurements ($M_1, M_2,$ and $M_3$) and lookup table ($LT$), and it returns three outputs ($\hat{S}_1, \hat{S}_2,$ and $\hat{S}_3$) which are the BP sources concentrations estimates. The function $Find\_S$ is based on matlab interpolation function interp1 [29]. Any measurement value which lays in the LT range and between two LT rows is linearly interpolated to obtain the BP source concentration. The final BP sources concentration are obtained from a descending sub-lookup tables order. The LT retrieve algorithm follows the steps:

- Find $S_1 = x$ based on $M_1$
- Find $S_2 = y$ based on $S_1$ sub-lookup table and $M_2$
- Find $S_3 = z$ based on $S_2$ sub-lookup table and $M_3$

Figure 7 clarifies the LT construction algorithm. The second algorithm which retrieves the estimated BP sources concentrations from the LT using interpolation technique is concisely given in Algorithm 2.

It is important to mention, that the actual implementation of the proposed algorithms and conditions is quite complex.

![FIGURE 7. Retrieving BP sources concentrations from the LT.](image-url)

IV. RESULTS AND DISCUSSION

In this section, the proposed LT based BP estimation method results are analyzed. The method is evaluated based on the absolute error between the actual concentration (obtained from BP model) and the estimated BP concentration (obtained from the LT technique). Then the proposed method is compared with three other techniques. After that, it is implemented to a larger network. Finally, the proposed BP estimation method is tested under variations in BP measurements and network parameters.

A. METHOD EVALUATION

Three cases are studied to demonstrate the proposed LT method effectiveness. The first case considers exact measurements on the LT data. The second case considers approximate measurements on the LT. The third case considers approximate measurements in between LT data which are in this case interpolated. The LT results are summarized in Table 3. The absolute errors in all cases are small and acceptable. The method is implemented offline in a normal specs computer.

1) BP ESTIMATION METHODS COMPARISON

The major difference between the proposed LT method and other optimization methods is that optimization methods use iterative approach. In the iterative approach, the algorithm starts will initial guess then converge to the estimated value based on certain defined threshold. In this
TABLE 3. Results of the proposed LT based BP estimation technique.

| Case   | Measurements | Sources | Estimations | |Error|
|--------|--------------|---------|-------------|--------|
| Case-1 | M₁=LT(95.1)  | S₁=5.00 | S₁=5.0000   | e₁=0.0000 |
| M₂=LT(95.2) | S₂=9.00 | S₂=9.0000 | e₂=0.0000 |
| M₃=LT(95.3) | S₃=0.00 | S₃=0.0000 | e₃=0.0000 |
| Case-2 | M₁=0.8470   | S₁=10.0 | S₁=9.9995   | e₁=0.0005 |
| M₂=0.1921 | S₂=5.00 | S₂=4.9986 | e₂=0.0014 |
| M₃=0.9016 | S₃=2.00 | S₃=2.0080 | e₃=0.0080 |
| Case-3 | M₁=0.8045   | S₁=9.50 | S₁=9.4997   | e₁=0.0003 |
| M₂=0.1523 | S₂=3.50 | S₂=3.4979 | e₂=0.0021 |
| M₃=0.3589 | S₃=0.02 | S₃=0.0205 | e₃=0.0005 |

FIGURE 8. Iterative algorithm.

The iterative algorithm starts with an initial BP sources concentration value which is inserted into the BP model. The resultant BP measurement value is compared with the input measurement. Then the error will be calculated. If the calculated solution does not satisfy the termination criterion, an updated BP source concentration is inserted into the BP model. Otherwise, the algorithm stops and returns the final estimation result. The termination criterion can be a fixed number of iterations or error value (the difference between estimated and input BP measurements concentration).

The results of four BP estimation techniques, which are genetic algorithm (GA), particle swarm optimization (PSO), interior point method (IPM), and lookup table (LT) for Case 3 in Table 3 are summarized in Table 4. It can be noted that the results of each method are different in terms of absolute error and simulation time. The absolute error value is good in all cases, but the main difference is in the time required to retrieve the estimated BP concentration values. The proposed LT method has the smallest simulation time.

2) METHOD EVALUATION ON A LARGER NETWORK

In the previous subsection, the proposed LT method is explained and evaluated for a small network, but it is also valid for larger natural gas networks. The BP data is variable, and it changes by many factors such as network, geographical, and weather properties. Thus, very few data of BP concentration in natural gas networks has been reported in the literature [31]. The proposed BP sources concentrations estimation strategy is applied to a larger natural gas pipeline network. The topology of this network is similar to the one shown in Figure 2, and its geometric parameters are available in Table 6.

TABLE 4. BP estimation methods results comparison.

| Method  | (GA) [18] | PSO [19] | IPM [18] | LT |
|---------|-----------|----------|----------|----|
| Error   | e₁=0.0007 | e₂=0.0005 | e₁=0.0002 | e₁=0.0003 |
| e₂=0.0039 | e₂=0.0043 | e₂=0.0019 | e₂=0.0021 |
| e₃=0.0017 | e₃=0.0002 | e₃=0.0006 | e₃=0.0005 |
| Time    | ≈ 2.1 hours | ≈ 1.8 hour | ≈ 1.2 hour | < 0.5 seconds |

TABLE 5. BP estimation methods features and limitations.

| Features | Limitations |
|----------|-------------|
| Lookup table | - Lower estimation time |
| - Lower computations |
| - Less tuning parameters |
| Optimization | - Range is critical |
| - Higher estimation time |
| - Higher calculations |
| - Tuning parameters |

It is also important to mention that the solution of the proposed LT-based approach is unique, and it is valid if and only if the number of measurements devices is equal to the unknown sources [30].
The simulation results are presented in Table 8. These results are divided into three tests. Each test represents a BP range in the LT. All tests have the same concentration range [0, 10] but the concentration increment is different. The first test has increment of 1, the second test has increment of 5, and the last test has increment of 10. For example, the BP sources concentration ranges in the second test are 0, 5, and 10 respectively. The LT construction time for Test-3 is the smallest, but the estimation accuracy is the lowest. The three tests show the trade-off between the LT BP concentrations range and accuracy.

**B. UNCERTAINTY STUDY**

To discuss the effectiveness of the proposed BP estimation algorithm, it is tested under two situations which are BP measurements uncertainty and network parameters uncertainty. The uncertainty studies are implemented to the small network for simpler illustrations. Firstly, the algorithm is applied to the same gas pipeline network shown in Figure 2, where the measurements of BP concentration at the client are not accurate. Secondly, the algorithm is tested under situations of model mismatch. Uncertainties in pipes roughness, mass flow rate, and gas density are investigated.

1) **UNCERTAINTY IN BP MEASUREMENTS**

This test aims to mimic the effect of measurements devices tolerance. In practical situations, the BP measurements devices are not 100% accurate, and there will always be a mismatch between real and measured values. The proposed estimation method should estimate BP sources concentration with low measurements sensitivity. The measurements uncertainty study is conducted on BP measurements ($M_1$, $M_2$, and $M_3$). It includes both positive and negative changes, and each individual measurement varies between $+50\%$ and $-50\%$. The BP measurements and sources from Case-2 in Table 3 are used. The relationship between a single BP measurement uncertainty and BP sources estimation is shown in Figure 9. The uncertainty test shows that the mismatches in the first BP measurement $M_1$ affect the second but not the last BP measurement as shown in Figure 9(a).
The uncertainty response of the second BP measurement $M_2$ is shown in Figure 9(b). Only the second and third BP sources are affected. Uncertainty in the third BP measurement $M_3$ does not affect the estimation of first and second BP sources as shown in Figure 9(c). Small amounts of uncertainty in BP measurements have acceptable margin. These results are reasonable based on the network properties and assumptions. Furthermore, higher uncertainty percentages lead to estimation errors because the resultant data may be out of the LT range. The same behavior is recorded for larger networks.

2) UNCERTAINTY IN NETWORK PARAMETERS

In this parameters variation study, a change in natural gas pipelines parameters is applied. The LT is constructed based on ideal parameters, and the uncertain BP measurements are used in the proposed BP estimation method. The small natural gas pipeline network parameters are available in Table 1. The large LT range is used in all tests, for smaller range leads to higher BP sources concentrations estimation errors. The network parameters uncertainty study results are
summarized in Table 9. The main parameters of the natural gas pipeline network which are pipe roughness, mass flow rate, and gas density are examined. The uncertainty tests consider different percentages and pipes. This includes high and low positive and negative test values. Typically, it is rare that the variation in model parameters exceeds ±10%. High uncertainty percentages are used to see the effect of extreme cases on the proposed BP estimation technique. It can be noted from Table 9 that the BP sources concentration estimation depends on the network parameters. Uncertainties in different parameters have unlike effects on BP estimation. The uncertainty percentages are proportional to the BP estimation error. In addition, the uncertainty in more than one pipe and network parameter has higher impact on BP sources concentration estimation. The uncertainty studies show that the proposed LT based BP estimation method is a feasible way to estimate the BP concentrations in natural gas pipeline networks. BP estimation accuracy depends on measurements and network parameters. The closer the parameters the better the BP estimation. Also, the LT should be updated or reconstructed based on new network inputs or parameters in order to achieve better BP concentrations estimation. All in all, the proposed method results are convenient for natural gas network operators to get a valuable relative assessment for BP sources concentrations in natural gas pipeline networks.

V. CONCLUSION

Through the simulation studies, the proposed LT-based BP concentrations estimation method has been validated as a good technique to identify BP concentration under different situations of ideal measurements, disturbed measurements, and model uncertainty variations. The proposed method is compared with three optimization-based methods. The results of the proposed LT-based method show accurate and fast BP sources concentration estimation. The main limitation of this method is that the BP measurements must be in the LT range. For example, an unexpected BP measurement may occur out of the generated LT range, and estimating it will not be possible. Thus, the LT range must be selected carefully considering high BP concentration ranges as well as estimation accuracy. The proposed LT method can be further enhanced and extended in the following aspects:

- **Model improvements:** for instance, pick up case can be considered to model the movement of BP particles, variant size of BP particles can be used, and other pipeline topology [32] can be studied.
- **LT enhancements:** advanced LT table techniques such as nonlinear interpolation can be used to enhance the proposed BP estimation method accuracy.
- **New methods:** for example, future study can focus on finding a combined method between lookup table and optimization techniques to improve BP estimation time and accuracy.

- **Code optimization:** the code can be further optimized to reduce the LT construction time as well as increase the BP estimation accuracy.
- **Real BP measurements:** currently there are BP measurements devices installed in a real natural gas network in the Emirate of Abu Dhabi. These measurements are continuously stored and analyzed and will be used to further validate the proposed BP estimation technique.
- **Real-time implementation:** real-time natural gas network parameters and BP measurements will be used to update the proposed estimation method online.

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