

# Research on Internal Parameter Filtering of Natural Gas Pipeline under Duty Cycle Transmission Mechanism

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## Abstract

In recent years, with the continuous growth of China's long-distance oil and gas pipeline network, wireless communication network applications have become more and more extensive with the continuous promotion of intelligent oilfield construction, while the energy-saving problem in the process of information transmission has become increasingly prominent. In order to ensure the sustainable development of China's oil and gas industry, low-power wireless transmission has become a basic requirement for the current intelligent oil and gas pipeline communication construction. For the monitoring of pipeline operating conditions, pressure and flow rate values are important parameters. If the accuracy and comprehensiveness of pipeline operation data can be ensured simultaneously under an energy-efficient transmission mechanism, it will provide strong support for the green and safe operation of pipelines. Therefore, in this paper, a recursive filtering study is conducted for natural gas gathering pipeline flow system under duty cycle transmission mechanism to complete the reliable monitoring of pipeline fluid transportation status.

## Keywords

Natural Gas Pipeline Flow System; Duty Cycle Transmission Mechanism; Recursive Filtering; Collaborative Filtering.

## 1. Introduction

Considering the current low-carbon and energy-saving goals in smart oil and gas pipelines, this paper introduces an energy-saving wireless transmission mechanism, the Duty Cycle Transmission Mechanism (DCTM), in the communication process[1]. DCTM can also be applied to occasions with low network bandwidth and limited channel capacity, which can not only reduce the energy consumption of the communication process, but also prolong the service life of sensor nodes. But on the other hand, high energy saving may induce increased sparsity of measurement data, which affects filter performance. To solve this problem, this paper introduces the Collaborative Filtering (CF) algorithm to predict the sparse data, and uses the compensated complete data as the measurement input of the filter. So far, this paper presents a new recursive filtering algorithm combined with CF algorithm under DCTM[2]. To ensure the performance of the designed filter, the error covariance matrix is derived and its upper bound is proved to be bounded. The gain matrix of the designed filter is then further obtained by minimizing the trace of the error covariance matrix. And through MATLAB simulation, it is verified that the given filtering scheme can effectively estimate the internal parameters of natural gas pipelines under the premise of saving energy. The excellent performance of the recursive filtering algorithm given in this paper is fully verified.

## 2. Problem Formulation and Preliminaries

The actual parameters of the pipeline in this paper are: the inner diameter of the pipeline is 0.5 m, the length of the pipeline is 2 km, the vertical distance between the pipeline and the horizontal plane is 2 m, and the natural gas flow in the pipeline is a constant temperature flow of 16.85°C, the absolute roughness of the pipeline is given as 42 μm, the Reynolds number of the pipeline is taken as 2500 in this paper for the transition state, and the natural gas wave velocity in the pipeline is 400 m/s. Combining with the literature [3] and [4], a parameterized discrete state space model of the natural gas pipeline flow system can be given as below:

$$\begin{cases} x_{k+1} = A_1^* x_k + B_1^* u_k + w_k, \\ y_k = Cx_k + Du_k + v_k, \\ z_k = Cx_k + Du_k, \end{cases} \quad (1)$$

The coefficient matrix is as follows:

$$\begin{aligned} A &= \begin{bmatrix} 0.9629 & 0 & 0 & 0 \\ 0 & 0.9752 & 0 & 0 \\ 0 & 0 & 0.9752 & 0 \\ 0 & 0 & 0 & 0.9813 \end{bmatrix}, B = \begin{bmatrix} 0.0372 & 0 \\ 0.0248 & 0 \\ 0 & -0.2437 \\ 0 & 0.0187 \end{bmatrix}, \\ C &= \begin{bmatrix} 1 & 0 & -1.0297 & 0 \\ 0 & -0.2054 & 0 & 1 \end{bmatrix}, D = \begin{bmatrix} 0 & -19.9166 \\ 0.2054 & 0 \end{bmatrix}. \end{aligned} \quad (2)$$

where,  $x_k = [x_1, x_2, x_3, x_4]^T$  is the state variable of this discrete system,  $u_k = [P_{in}, M_{out}]^T$  is the known input to the system, the known inlet pressure and outlet flow rate of the natural gas pipeline. A, B, C, and D are the coefficient matrices of the discrete system of the pipeline in the appropriate dimension,  $y_k = [P_{out}, M_{in}]$  is the measured output,  $z_k = [\hat{P}_{out}, \hat{M}_{in}]$  is the measured output to be estimated[5].  $w_k \in R^n$  and  $v_k \in R^m$  are process noise and measurement noise, respectively. Process noise is a comprehensive abstract description of uncertainty and random perturbations in the model building process, and measurement noise is a sampling description of noise in the data sampling process[6]. It is found that engineering noise mostly belongs to zero-mean Gaussian white noise, so we assume that process noise  $w$  and measurement noise  $v$  are independently distributed, and their normal distribution is as below:

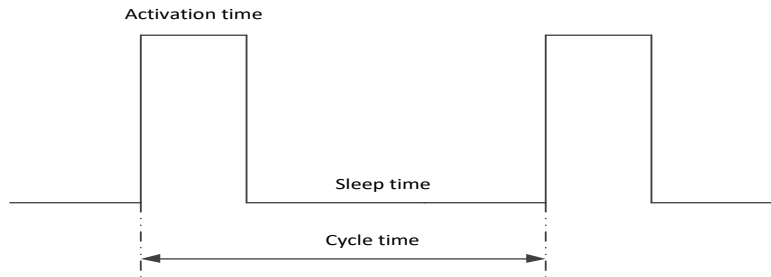
$$\begin{aligned} w(k) &\sim N(0, Q_{w,k}) \\ v(k) &\sim N(0, R_{v,k}) \end{aligned} \quad (3)$$

The two are independent of each other and both have a mean of 0, corresponding to covariances of  $Q_{w,k}$  and  $R_{v,k}$ , respectively.

### 2.1. Mathematical Modeling of DCTM[1]

The relationship between activation time, sleep time and sleep activation cycle time is shown in Figure 1. The sensor node sends data periodically according to the preset duty cycle. In this paper, a natural gas pipeline network system with multiple wireless sensor nodes is considered, and a duty cycle communication protocol is used for data transmission. Specifically, the

mathematical model of the duty cycle transmission mechanism can be understood in detail by the literature of [1].



**Figure 1.** Relationship between activation time, sleep time and cycle time

According to the spatial distribution of sensor nodes in the actual project, numerous wireless sensors can be grouped into  $M$  nodes. To simplify the problem and facilitate theoretical analysis, the measured output before transmission can be rewritten as follows:

$$y_k = [y_{1,k}^T, y_{2,k}^T, \dots, y_{M,k}^T]^T \tag{4}$$

where,  $y_{i,k}$  ( $i = 1, 2, \dots, M$ ) represents the measured value of the  $i$ th node at moment  $k$ . From the previous section, it is known that the measured output will not be sent when the sensor node is placed in the sleep state.

The measurement output after transmission through the communication network is as follows:

$$\tilde{y}_k = [\tilde{y}_{1,k}^T, \tilde{y}_{2,k}^T, \dots, \tilde{y}_{M,k}^T]^T \tag{5}$$

where  $\tilde{y}_{i,k}$  ( $i = 1, 2, \dots, M$ ) denotes the measurement output of the  $i$ th node at moment  $k$  after transmission through the communication protocol. That is, the measurement output before transmission through the communication protocol is  $y_k$  and the measurement output after transmission through the communication protocol is  $\tilde{y}_k$ . Therefore the rules for updating  $\tilde{y}_k$  are as follows:

$$\tilde{y}_k = A_k y_k \tag{6}$$

where  $A_k$  represents the diagonal matrix,  $A_k = \text{diag}\{\lambda_{i,k}\} (i = 1, 2, \dots, M)$  and has the following expression:

$$\lambda_{i,k} = \begin{cases} 1, & \text{if } \frac{\text{mod}(k, T_c^i)}{T_c^i} \leq d_c^i \text{ and } k \geq 0 \\ 0, & \text{else} \end{cases} \tag{7}$$

where  $T_c^i$  and  $d_c^i$  represent the cycle time as well as the duty cycle of the  $i$ th sensor, respectively. The duty cycle is expressed as:

$$d_c^i = \frac{T_a^i}{T_c^i} \tag{8}$$

$T_a^i$  denotes the activation time of node i. Correspondingly,  $T_c^i$  denotes the cycle time of node i. Under the duty cycle communication mechanism, the measurement output received after transmission follows the update rules described in equations (5)-(8). First, equation (7) is used to determine the current state that the sensor node is in. If  $\frac{\text{mod}(k, T_c^i)}{T_c^i} \leq d_c^i$  and  $k \geq 0$ , that is, it indicates that the  $i$ th sensor node is in the moment  $k$  is in the activation time, which can be obtained according to equations (6) and (7),  $\tilde{y}_k = y_k$ . Otherwise, the moment  $k$  is within the dormant time period, when the sensor node  $i$  stops working and does not receive and send data, then  $\tilde{y}_k = 0$ . Therefore, the main work of the author is to compensate the measurement data that are not sent at the dormant moment by using the prediction algorithm, and to ensure the accuracy and low energy consumption of the prediction compensation.

### 2.2. Recursive Filtering based on Collaborative Filtering Algorithm

In the context of this paper, the "item" in the item-based collaborative filtering algorithm (IBA) corresponds to the moment when the data is transmitted in the conventional transmission mode of the sensor, and the "user's rating of the item" corresponds to the measured value of the sensor. This method can be used to predict the sensor's unsent data for the case of data sparsity induced by the duty cycle communication mechanism during wireless transmission. In this paper, for example, this method is applied to predict the pressure and flow parameters not sent by the sensor in order to compensate for the sparse data received at the filter end[7]. Throughout this paper,  $\hat{y}_k$  denotes the prediction that the sensor node did not send an output at moment  $k$ :

$$\hat{y}_k = [y_{1,k}^T, y_{2,k}^T, \dots, y_{M,k}^T]^T \tag{9}$$

where  $\hat{y}_{i,k}, (i = 1, 2, \dots, M)$  is the prediction of the measurement output, when the sensor node  $i$  is in a dormant state at moment  $k$  without transmitting, and has:

$$\hat{y}_{i,k} = \bar{Y}_k + \frac{\sum_{\lambda \in \Omega_N} Sim_{k\lambda} (y_{i,\lambda} - \bar{Y})}{\sum_{\lambda \in \Omega_N} |Sim_{k\lambda}|} \tag{10}$$

where  $\Omega_N$  represents the set of nearest neighbors similar to the measurement output at moment  $k$ .  $y_{i,k}$  represents the measurement output of sensor node  $i$  at moment  $k$ [8].  $\bar{Y}_k$  and  $\bar{Y}_\lambda$  represent the average value of the measurement output at moment  $k$  and at moment  $\lambda$ , respectively.  $Sim_{k\lambda}$  represents the similarity between the measurement output at moment  $k$  and at moment  $\lambda$ , which is calculated as follows.

$$Sim_{k\lambda} = \frac{\sum_{j \in \Omega_{k\lambda}} (y_{j,k} - \bar{Y}_k)(y_{j,\lambda} - \bar{Y}_\lambda)}{\sqrt{\sum_{j \in \Omega_{k\lambda}} (y_{j,k} - \bar{Y}_k)^2} \sqrt{\sum_{j \in \Omega_{k\lambda}} (y_{j,\lambda} - \bar{Y}_\lambda)^2}} \quad (11)$$

where  $\Omega_{k\lambda}$  is the set of nearest neighbors of the sensor nodes that send data at  $k$  and  $\lambda$  moments,  $y_{j,k}$  and  $y_{j,\lambda}$  represent the measurement outputs sent by the  $j$ th sensor node at  $k$  and  $\lambda$  moments, respectively. In this paper, we use the Top-N method. The Top-N method is based on the obtained similarity, the target users may be interested in some items, and then recommend a set of  $N$  highest ranked items [9,10].

Define the measurement output received by the filter as follows.

$$\bar{y}_k = A_k y_k + (I - A_k) \hat{y}_k, \forall k \geq 0 \quad (12)$$

### 3. Main Results

#### 3.1. Filter Design

In this paper, a Kalman filter method is designed to solve the state estimation problem of the system under duty cycle transmission mechanism, and the filter design is as follows.

$$\begin{cases} \hat{x}_{k+1|k} = A \hat{x}_{k|k} + B u_k \\ \hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + K_{k+1} (\bar{y}_{k+1} - A_k (C \hat{x}_{k+1|k} + D u_{k+1})) \end{cases} \quad (13)$$

Theorem 1: The one-step prediction error covariance matrix  $P_{k+1|k}$  and the filtering error covariance matrix  $P_{k+1|k+1}$  satisfy the following two recursive equations.

$$P_{k+1|k} = A P_{k|k} A^T + Q_{w,k} \quad (14)$$

$$\begin{aligned} P_{k+1|k+1} &= (I - K_{k+1} \Lambda_{k+1} C^*) P_{k+1|k} (I - K_{k+1} \Lambda_{k+1} C^*)^T \\ &+ K_{k+1} \Lambda_{k+1} Q_{v,k} \Lambda_{k+1}^T K_{k+1}^T + K_{k+1} (I - \Lambda_{k+1}) \hat{r}_{k+1} \hat{r}_{k+1}^T (I - \Lambda_{k+1})^T K_{k+1}^T \end{aligned} \quad (15)$$

For detailed pushback see literature [1].

Theorem 2: In the case where the one-step prediction error covariance matrix and the filter error covariance matrix are known, the filter gain matrix  $K_{k+1}$  is obtained by minimizing the trace of the filter error covariance matrix as follows.

$$\begin{aligned} K_{k+1} &= P_{k+1|k} C^T \Lambda_{k+1}^T \Theta_{k+1}^{-1} \\ \Theta_{k+1} &= \Lambda_{k+1} C P_{k+1|k} C^T \Lambda_{k+1}^T + \Lambda_{k+1} Q_{v,k} \Lambda_{k+1}^T + (I - \Lambda_{k+1}) \hat{r}_{k+1} \hat{r}_{k+1}^T (I - \Lambda_{k+1})^T \end{aligned} \quad (16)$$

Proof: Taking the partial derivative of the covariance matrix  $P_{k+1|k+1}$  with respect to  $K_{k+1}$  and letting it be 0, has the following expression:

$$\begin{aligned} \frac{\partial \text{tr}(P_{k+1|k+1})}{\partial K_{k+1}} &= -2P_{k+1|k} C^T A_{k+1}^T + 2K_{k+1} A_{k+1} R_{v,k+1} A_{k+1}^T \\ &+ 2K_{k+1} A_{k+1} C P_{k+1|k} C^T A_{k+1}^T + 2K_{k+1} (I - A_{k+1}) \hat{y}_{k+1} \hat{y}_{k+1}^T (I - A_{k+1})^T \\ &= 0 \end{aligned} \quad (17)$$

From this, the filter gain matrix  $K_{k+1}$  can be found. The theorem is proved.

### 3.2. Bounded Analysis of Error Covariance

Next, the performance of the filtering algorithm designed in this paper will be analyzed by proving the boundedness of the upper bound of the error covariance matrix.

Assumption 1: For any moment  $k$ , there exists some positive scalar as follows.

$$\underline{a}, \bar{a}, \underline{b}, \bar{b}, \underline{c}, \bar{c}, \underline{q}_w, \bar{q}_w,$$

such that for any  $k$  satisfying:

$$\begin{aligned} \underline{q}_w &\leq \|Q_{w,k+1}\| \leq \bar{q}_w, \underline{a} \leq \|A\| \leq \bar{a}, \\ \underline{b} &\leq \|B_k\| \leq \bar{b}, \underline{c} \leq \|C\| \leq \bar{c}. \end{aligned}$$

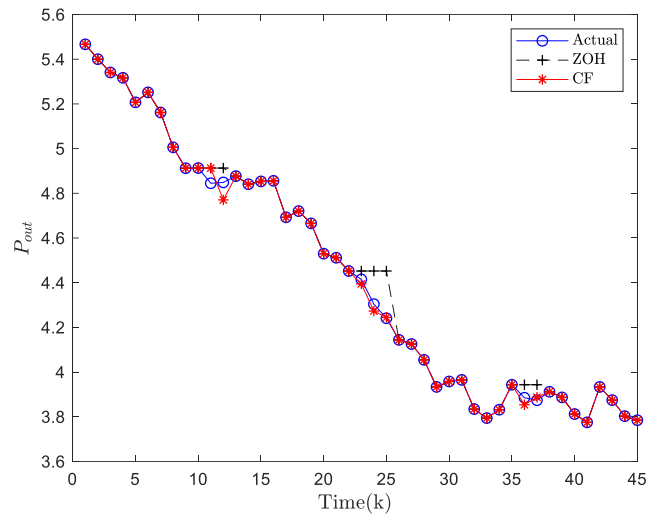
Theorem 3: Based on Assumption 1, the upper bound of the filtering error covariance matrix is as follows:

$$P_{k+1|k} \leq \varepsilon_1 P_{0|0} + \varepsilon_2 I \quad (18)$$

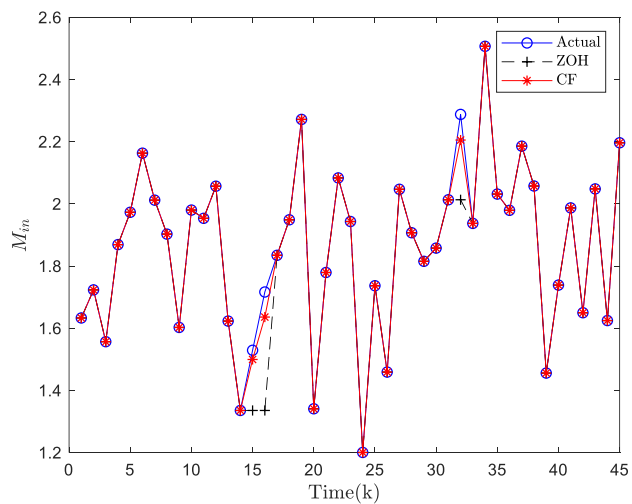
$$P_{k+1|k+1} \leq P_{k+1|k} \quad (19)$$

## 4. Numerical Example

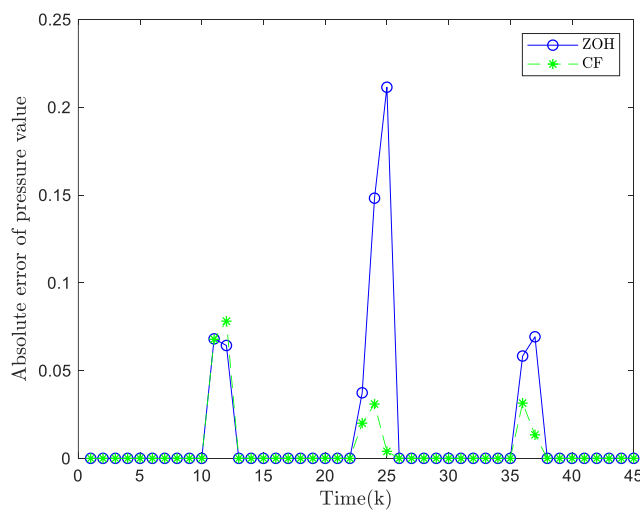
Consider the natural gas pipeline flow system described in equation (1), the corresponding coefficient matrix of this system is shown in equation (2). In the case of sparse data, we consider replacing the unsent outputs with the corresponding predictions. Next, the superiority of the adopted collaborative filtering algorithm under the duty cycle communication mechanism will be verified by comparing it with the zero-order keeper prediction method. Let the covariance matrices of process noise  $w_k$  and measurement noise  $v_k$  be  $Q_{w,k} = 0.04I$  and  $R_{v,k} = \text{diag}\{0.07, 0.05\}$ , respectively. The initial state is set to  $x_0 = [7.5, 6, 2.5, 2]^T$  according to the actual situation. The activation time of the pressure sensor node is  $T_a^1 = 8s$ , the cycle time is  $T_c^1 = 10s$ , and the duty cycle is  $d_c^1 = 0.8$ ; the activation time of the flow sensor node is  $T_a^2 = 5.85s$ , the cycle time is  $T_c^2 = 6.5s$ , and the duty cycle is  $d_c^2 = 0.9$ . Figures 2 and 3 respectively plot the actual output value of the sensor node under DCTM, the predicted value using the ZOH and CF, and it can be preliminarily judged that the pressure value and flow value predicted by the collaborative filtering algorithm are different from the actual output value. value is relatively close. Figures 4 and 5 plot the absolute errors of predicted and actual output values in terms of ZOH and CF, respectively. Obviously, compared with the ZOH method, the CF algorithm achieves a more accurate prediction of the unsent data from the sensor nodes.



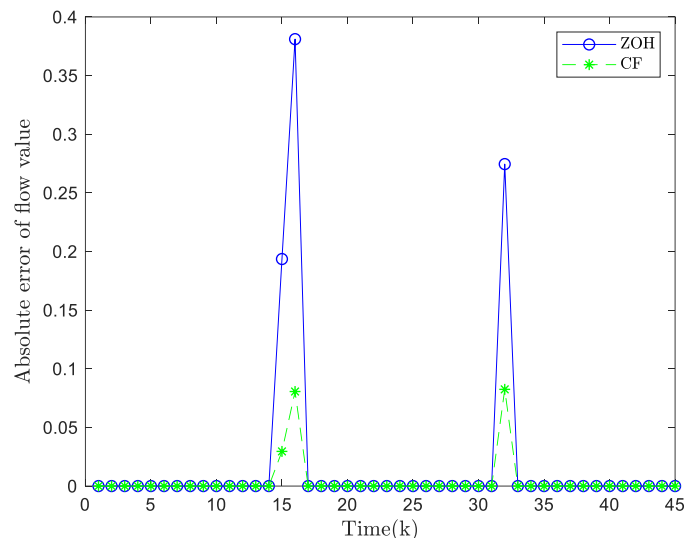
**Figure 2.** Actual, ZOH and CF predicted values of outlet pressure



**Figure 3.** Actual, ZOH and CF predicted values of inlet flow



**Figure 4.** Absolute errors of ZOH and CF prssure predictions



**Figure 5.** Absolute errors of ZOH and CF flow predictions

## 5. Conclusion

This paper takes the current intelligent natural gas pipeline network construction as the background, fully considers the basic production requirements of energy saving and consumption reduction in the oilfield field, and considers the energy saving in the process of wireless data transmission and receipt in the oilfield network under the scenario that many wireless sensor nodes for monitoring are applied to natural gas pipelines in the oilfield. To estimate the state of the natural gas pipeline transmission medium as accurately and comprehensively as possible under the duty cycle based wireless transmission mechanism for leak detection of oil and gas pipelines and other related work. with the aim of ensuring safe pipeline operation, the recursive filtering problem of natural gas pipeline flow system is studied.

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