

Detection and Location for Slow Leakage of Oil Pipeline

Based on Weighted Logical Inference and Data Fitting

Xuguang Hu¹, Dazhong Ma¹, Qiuye Sun¹

1. College of Information science and engineering, Northeastern University, Shenyang 110004

E-mail: madzmadz4230@gmail.com

Abstract: A leakage location method for oil pipeline based on weighted logical inference and data fitting (WLIDF) is proposed, which can decrease the number of false alarms and improve accuracy of slow leakage detection and location. According to the running parameters, the running model of oil pipeline can be decided based on weighted logical inference, which can give a solution under situation of compact representations for multi-valued uncertain causalities and incomplete information. When the leakage happened, the data fitting is used to decide the location and time of the leakage. According to the method of WLIDF, the slow leakage can be found on time and the position of the leakage point can be accuracy located. The simulation and application shows the effective and good performance of the proposed methods.

Key Words: Data Driven Method, Slow Leakage Detection, Weighted Logical Inference, Data Fitting

1 INTRODUCTION

In recent years, it was difficult to establish accurate mathematical models of industrial process because modern industry become more complex and large-size than ever. An method called data-driven is proposed to solve problems by taking advantage of data, including the operation and the fault states, which are produced and stored in the industry production process^[1]. Data-driven method does not need build accurate model to control and diagnosis working conditions and it has good performance. And Data-driven method has been used in many aspects, such as copper flash smelting process^[2] and fault diagnosis^[3].

There are a plurality of methods for detecting leakage of fluid conveying pipelines, it includes sound-wave-based method, pressure point analyzing method, negative pressure wave method, etc^[5-11]. Systems for detecting pipeline leakage based on negative pressure wave have been widely used, but this kind of systems still have some common problems at present: firstly, missed alarm rate of small amount of leakage and slow leakage is high; secondly, the resistance of the systems against working condition disturbance is not strong, and false alarm rate is high; thirdly, slow leakage is not often detected by current detection methods.

In order to overcome the disadvantage of current problems, many people put forward the solutions. In [12], an intelligent detection method based on fuzzy classification is used to leakage fault. But this method needs a lot of variables to establish model. In [13], it presents a novel pipeline leakage detection scheme based on a state coupling analysis. But

This work is supported by National Nature Science Foundation under Grant 61203086, 61573094, Doctoral Fund of Ministry of Education of China 20120042120042 and the Fundamental Research Funds for the Central Universities N130404009, N140402001.

sometimes it misses slow leakage. In [14], harmonic wavelet method is applied to small leakage, but it may cause increase alarm. In [15], it uses expert systems to train and use for pipeline leak detection and enhances the accuracy of leakage detection.

After analyzing pipelines characters, it is proposed to detect and locate pipeline leakage with data driven method. Pipeline running model is built based on weighted logical inference and the leakage position is calculated by data fitting.

By simulation and application, the method is proved that it can raise accuracy of finding slow leakage point and reduce the rate of positive error.

2 THE RUNNING MODEL OF PIPELINE BASED ON WLI

2.1 Weighted Logical Inference

Weighted logical inference (WLI) introduces a novel logic event inference algorithm that is accompanied by the algebraic operation of weighting factors^[19-21]. It provides a solution for effective and exact inference under situations of compact representations for multi-valued uncertain causalities and incomplete information.

It is used to identify operation condition and build multi-sensor data fusion model by WLI and Dynamic Uncertain Causality Graph (DUCG).

WLI theory model is showed in figure 1. Variables of each parent have a weight factor before connecting event, variables X_n is:

$$X_{n,k} = \sum_i \sum_{j_i} \left(\frac{r_{n,i}}{r_n} \right) A_{n,k;i,j_i} V_{i,j_i} \quad (1)$$

Where $X_{n,k}$ is the k-th state of X_n ; $r_{n,i}$ is the weight factor of variable V_i and X_n ; r_n is the sum of weight factors,

$r_n = \sum_i r_{n,i}$; $A_{n,k;i,j_i}$ means V_{i,j_i} independent trigger $X_{n,k}$; V_{i,j_i} is the j_i -th state of V_i ,and j replaces $j_i, V_i \in \{X, B, G\}$.

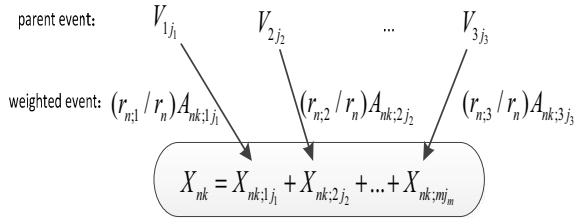


Fig. 1The theory model of weighted logical inference

In particular, weight $r_{n,i}$ is explained: $r_{n,i}$ is used to show whether X_n and V_i exists uncertain causal relationship. $r_{n,i} / r_n$ is the weight contribution of V_i to X_n probability. Because of $r_{n,i} / r_n$, $A_{nk;ij}$ probability reduce to $r_{n,i} / r_n$. It is worth mentioning that $A_{nk;ij}$ has equal weight $r_{n,i} / r_n$ if $k \neq j$ and $n=i$. Following equations have got by event algorithm:

$$\Pr\{X_{nk} | \bigcap_i V_{ij_i}\} = \sum_i (r_{n,i} / r_n) a_{nk;ij_i} \quad (2)$$

$$\begin{aligned} x_{nk} &\equiv \Pr\{X_{nk}\} = \sum_i (r_{n,i} / r_n) \sum_{j_i} a_{nk;ij_i} \Pr\{V_{ij_i}\} \\ &= \sum_i (r_{n,i} / r_n) \sum_{j_i} a_{nk;ij_i} v_{ij_i} \end{aligned} \quad (3)$$

Where $\Pr\{X\}$ means the probability of X happens; x_{nk} means the probability of X_{nk} happens. The others have same meanings with mentioned above.

2.2 The Running Model of Pipeline

Devices related to adjust operation conditions are shown in figure 2. In a typical station, It has hundreds of variables including sensors, control equipment and safety equipment, etc. So, establishing an accurate model is very difficult.

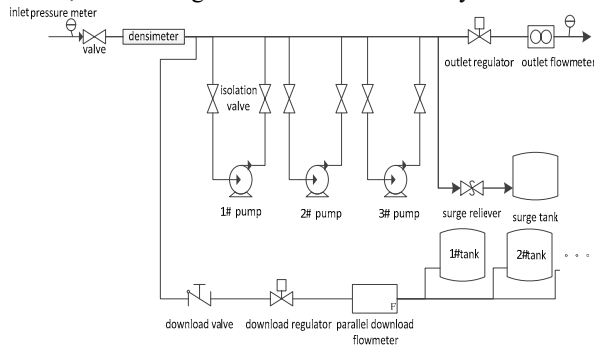


Fig. 2 Structure chart of typical monitor station

Building pipeline model uses WLI because it matches WLI's trait that the pressure change may be caused by different factors . After analyzing the operating conditions and historical data, it configures variables for leakage and the causal relationships between devices states and operating conditions ,as shown in figure 3.

When pipeline status is changed, conditional probability of adjusting operation condition that has max value is considered as pipe parameter's changing cause. False alarm rate could be reduced, because all pipe parameter's changing causes judging from WLI are blocked except leakage. If sensors data change, WLI will analyze working conditions during the process of running. The result of WLI is leakage when it is not operation condition adjustment, so WLIDF can detect slow leakage.

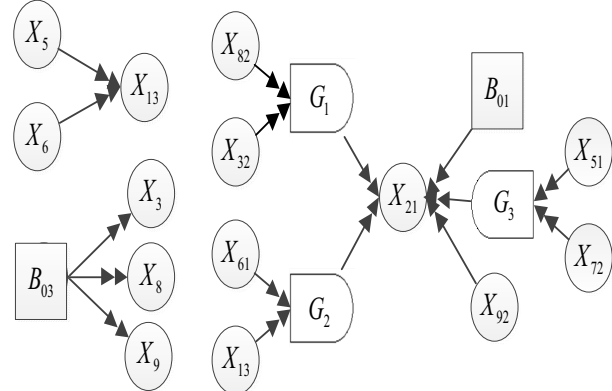


Fig. 3 Same effect variables' configuration

Where X_1 :pressure in oil pipelines, it has three states. $X_{1,1}$ means inlet pressure and outlet pressure drop simulta neously; $X_{1,2}$ means inlet pressure and outlet pressure increase concurrently ; $X_{1,3}$ means pressure increase or drop.

X_2 :outlet flow, it has two states. $X_{2,1}$ means outlet flow is increased,; $X_{2,2}$ has opposite meanings.

X_3 :download flow ,it has two states. $X_{3,1}$ means down- load flow is increased,; $X_{3,2}$ has opposite meanings.

X_4 :oil's density, $X_{4,1}$ means oil's density is increased, $X_{4,2}$ has opposite meanings.

X_5 :petroleum pump operation, $X_{5,1}$ means petroleum pump is opened , $X_{5,2}$ means petroleum pump is closed.

X_6 :outlet valve operation, $X_{6,1}$ means outlet valve is opened, $X_{6,2}$ means outlet valve is closed.

X_7 :relief valve operation , $X_{7,1}$ means relief valve is opened, $X_{7,2}$ means relief valve is closed.

X_8 :download regulating valve, $X_{8,1}$ means download regu- lating valve is opened, $X_{8,2}$ means download regulating valve is closed.

X_9 :oil tanks circumstance, $X_{9,1}$ means the number of oil tanks is increased, $X_{9,2}$ means the number of oil tanks is decreased;

B_{01} :pipeline leakage;

B_{02} :pipe network control;

B_{03} :Oil transportation scheduling.

3 THE LOCATION OF LEAKAGE BASED ON DATA FITTING

3.1 Angle Change Rule of Data Fitting

After pass through analyze a lot of pressure data, pressure change could express by data fitting. Figure 4 is the whole process curve of pressure drops in the ideal situation, and it divides into two areas to discuss the rules.

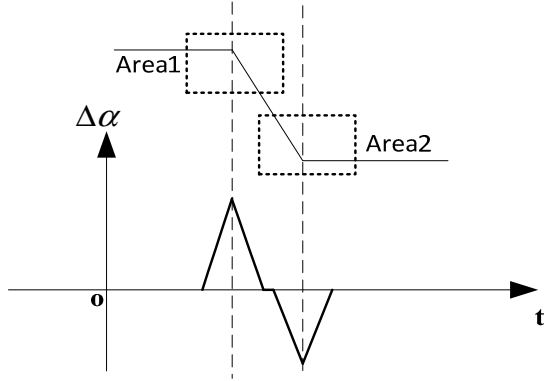


Fig. 4 Process of the angle change when pressure is dropping in ideal condition

This process has three steps which are from stable to decline to stable. In Figure 5, the data segment $A_iO_iB_i$ divides into two segments A_iO_i and O_iB_i , the angle is limited from 90° to 270° . Let angle A_iO_i and O_iB_i is α_1 , the difference of A_iO_i and O_iB_i is $\Delta\alpha = 0$. Angle O_iB_i is decreases until B_i exceeds O . Angle A_2O_2 is α_1 and O_2B_2 is α_2 , $\Delta\alpha = \alpha_1 - \alpha_2 > 0$. The difference of two angles reaches the maximum until O_2 becomes O , that is to say, $\Delta\alpha = \max$. After this, as the data segment moves forward, the difference is smaller, but $\Delta\alpha > 0$. Angle A_3O_3 and O_3B_3 is α_3 when A_3 is O . At this point, $\Delta\alpha = 0$, the state of stress is become stable.

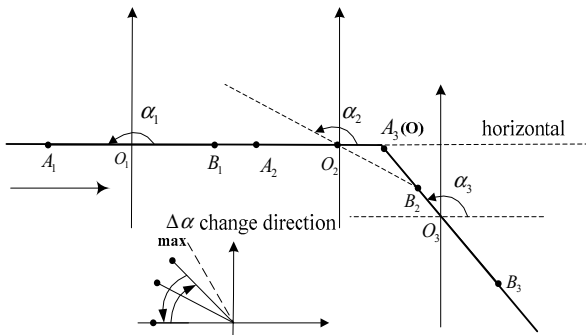


Fig. 5 Process of the angle change from the time when pressure is stable to the time when pressure is dropping

In a similar way, area2 has similar rule. Arrow represents the data movement, as shown in Figure 6. Likewise, the data segment $A_iO_iB_i$ divides into two segments A_iO_i and O_iB_i , the angle is limited from 90° to 270° . Let angle

A_iO_i and O_iB_i is α_1 , the difference of angle A_iO_i and O_iB_i is $\Delta\alpha = 0$. Angle O_iB_i is decreases until B_i exceeds O . Angle A_2O_2 is α_1 and O_2B_2 is α_2 , as shown in Figure 6, $\Delta\alpha = \alpha_1 - \alpha_2 < 0$. The difference of two angles reaches the negative maximum until O_2 becomes O , that is to say, $\Delta\alpha = -(\max)$. After this, as the data segment moves forward, the absolute difference is smaller, but $\Delta\alpha < 0$. Angle A_3O_3 and O_3B_3 is α_3 when A_3 is O . At this point, $\Delta\alpha = 0$, the state of stress is become stable.

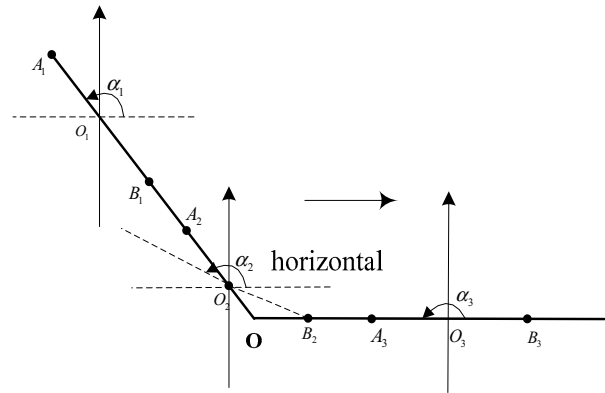


Fig.6 Process of the angle change from the time when pressure is dropping to the time when pressure is stable

The situation of horizontal steady state is showed in figures 5 and 6. Actually, it also exists other situations in the real situation that pressure is rising slowly and falling slowly. The figure 7 provides all situations in reality.

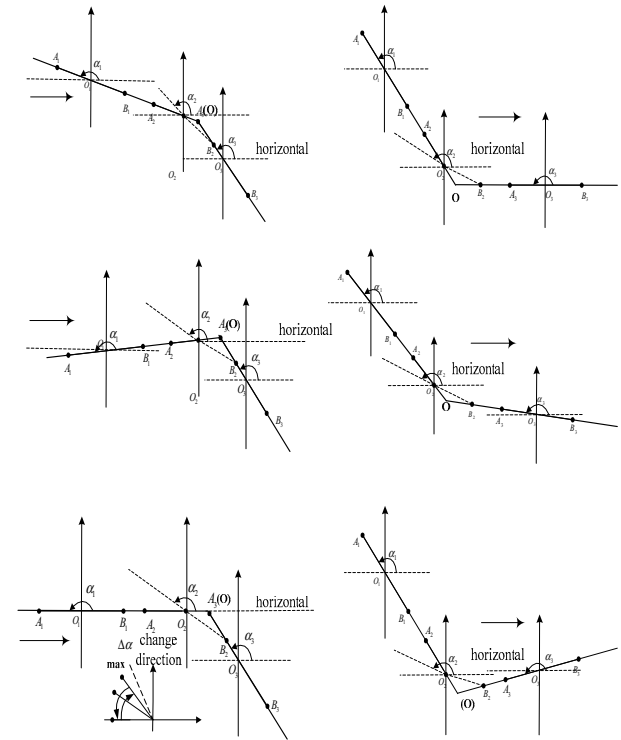


Fig.7 All kinds of processes of the angle change when pressure is dropping

Based on all of this discussion, it can be obtained that angle changing follows “small-big-small”. And if the angle range is $[90^\circ \ 270^\circ]$, the angle’s rule is right. From the rule , it can be found that the difference is max when the data segment’s midpoint overlaps with pressure wave’s inflection point. As to the analysis above, angle change can judge pressure down and acquire feature.

3.2 Location of The Leakage

From 3.1, it is known that angle changing follows “small-big-small” and pressure wave’s inflection point corresponds to the maximum value of angle change curve. In other words, angle change could be used to find pressure wave’s inflection point. After pressure drops, the difference of two inflection point time is the difference time of location, then the distance is calculated by location formula:

$$X_L = \frac{L(a-v) - \tau_0(a+v)(a-v)}{2a} \quad (4)$$

Where v is the flow velocity of the fluid in the pipeline; X_L is the distance from the leakage point to the inlet of the pipeline; τ_0 is the time difference. a is the wave velocity of the pressure wave.

In order to improve accuracy ,there are two problems to solve when data fitting as nonlinear mapping to analyze pressure curve.

Actual pressure curve fluctuates frequently is the first problem, so small fluctuations should become 0 in order to angle undulation is not too frequently. In this problem, a filtering window is introduced that the width is d . It sets to ‘0’ if angle change is less than d , otherwise it keeps the value. The drop point is more clear before process , which is in the figure 8.

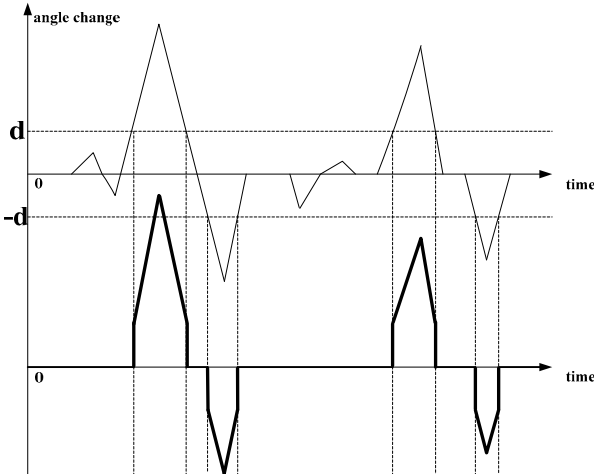


Fig.8 Show of the angle change based on data fitting

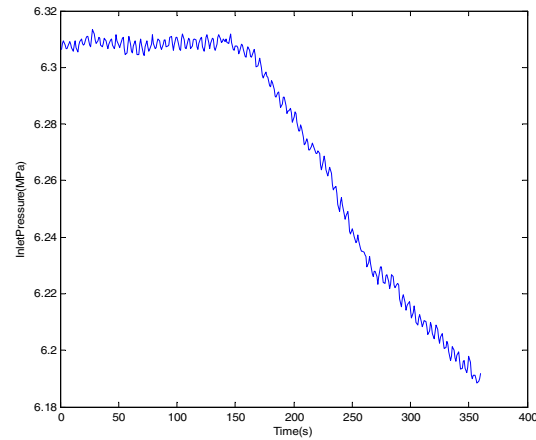
The parameter selection is the other problem. In the mapping process, suitable parameters were selected to adjust parameters dynamically and enhance the features. According to the experiment, the parameters are as follows: the length of data segment $A_i O_i B_i$ is $50 * 2 = 100$; The width of filtering window d is $\arctan(400 * \text{the min threshold of pressure drop} / \text{the length of fitting data segment})$, and the

angle’s difference is fit-slope times the experience coefficient(usually 100).

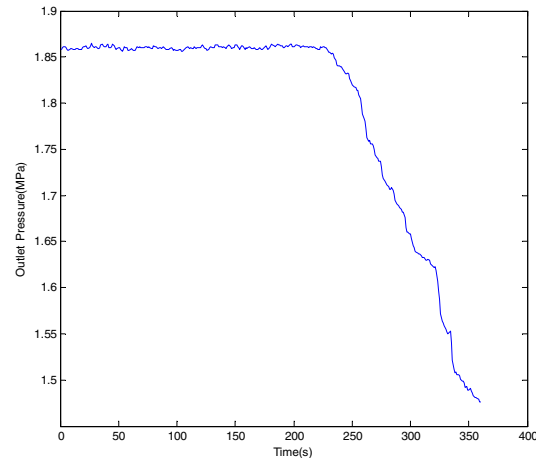
4 SIMULATION

The WLIDF judgment procedure is showed by simulation. The data is from actual slow leakage test data. It is used weighted logical inference to build model and judge pressure drops .When pressure drops ,it uses data fitting to find the position of leakage.

Step1:Obtain parameters. When pressure drops, pressure curve and other parameters should be got. In this problem, inlet and outlet pressure curve is showed in figure 9. From device state table ,it can be known that X1 is X11. X2 is X22, X3 is X31,X8 is X81and the others is not change.



(a) Pressure curve in the initial station



(b) Pressure curve in the final station

Fig.9 Pressure drop curve

Step2:Simplify model. Based on step1, extra variables and logic gates are removed and then simplified model is shown in figure 10.The relationships between changing variables are got in figure 10.

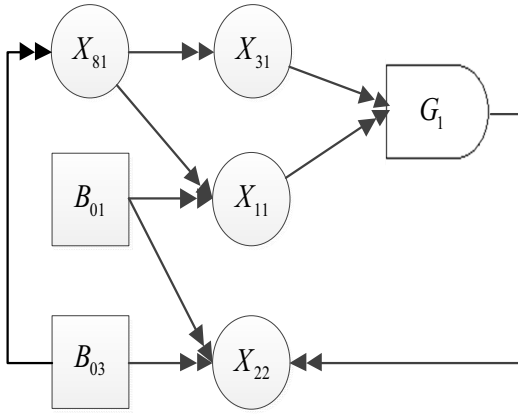


Fig. 10 Diagram of reduced model

Step3: Calculate probability density. After giving event parameters a and correlation r , probability density assignment can be calculated. Results status are obtained from simplified model. In this problem, $r_{n,i}$ is 1 for simplifying calculation. And the following equations are got from figure 10:

$$\begin{aligned} X_{11} &= \frac{1}{2} A_{11;01} B_{01} + \frac{1}{2} A_{11;81} X_{81} \\ &= \frac{1}{2} A_{11;01} B_{01} + \frac{1}{2} A_{31;81} A_{81;03} B_{03} \end{aligned} \quad (5)$$

$$\begin{aligned} X_{22} &= \frac{1}{3} A_{22;01} B_{01} + \frac{1}{3} A_{22;03} B_{03} \\ &\quad + \frac{1}{3} A_{22;G1} X_{31} X_{11} \end{aligned} \quad (6)$$

Replacing capitals with lowercase letters and plug values into equations (5) and (6):

$$1 = \frac{1}{2} a_{11;01} b_{01} + \frac{1}{2} a_{31;81} a_{81;03} b_{03} \quad (7)$$

$$1 = \frac{1}{3} a_{22;01} b_{01} + \frac{1}{3} a_{22;03} b_{03} + \frac{1}{3} a_{22;G1} \quad (8)$$

When putting coefficient matrix into the equation (7) and (8), The value of b_{01} and b_{03} are got.

Where Coefficient matrix is:

$$\bar{a}_{1,0} = \begin{bmatrix} 0.54 & - & - \\ - & - & - \\ - & - & - \end{bmatrix}, \quad \bar{a}_{2,0} = \begin{bmatrix} - & - & - \\ 0.6 & - & 0.7 \\ - & - & - \end{bmatrix},$$

$$\bar{a}_{2,G1} = \begin{bmatrix} - \\ 0.5 \end{bmatrix}, \quad \bar{a}_{3,8} = \begin{bmatrix} 0.5 & - \\ - & - \end{bmatrix}, \quad \bar{a}_{8,0} = \begin{bmatrix} - & - & 0.8 \\ - & - & - \end{bmatrix}.$$

Then the state is confirmed as leakage because $b_{01}=2.898$ and $b_{03}=1.087$.

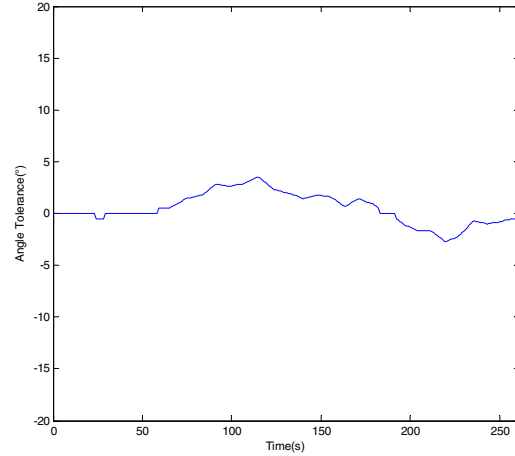
Step4: Fit data. After judging leakage, the next step is data fitting. Corresponding curve of the angle change is shown in figure 10.

It could know that the coordinates of pressure wave's inflection points are 165 and 228 from figure 9. In figure 11, the max value is 115 and 179, the points is corresponding to midpoint O .

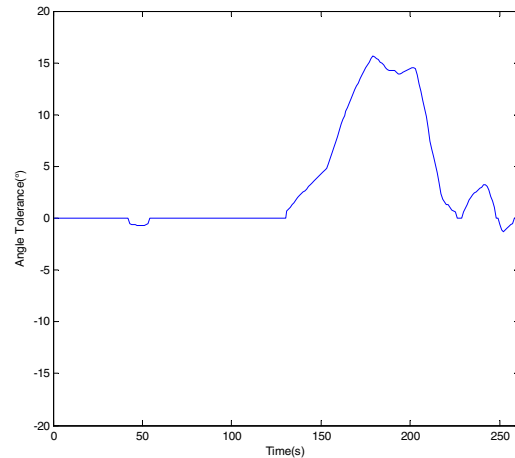
Step5: The leakage distance is calculated by equation (4) and it is 13 km.

The leakage distance is close to the real distance that is 13.5km. It's pretty well established that this method can be used in leakage location. In the simulation process, there are many times to change devices states like download valves and it is successful to block unnecessary information and reduce false alarm rate.

The simulation verifies the validity and feasibility of this method. And it also has good performance in practical application.



(a) Inlet pressure's angle tolerance



(b) Outlet pressure's angle tolerance

Fig. 11 Corresponding curve of the angle change

5 CONCLUSION

A leakage detection method which called WLIDF for solving the slow leakage problem has been proposed in this paper. The running model that can quickly identify leakage is proposed based on running parameters. The WLI theory provides a method for complex pipeline leakage model. When the pressure and flow changes, this model judges operating conditions through those changed parameters. If the running model judge leakage, the time and location of leakage are found by the data fitting. A simulation example is given to illustrate the effectiveness of the proposed method and it also has good performance in actual situation.

The future work will focus on improving the accuracy of the running model.

REFERENCES

- [1] Z.S. Hou, J.X. Xu, On Data-driven Control Theory: the State of the Art and Perspective, *Acta Automatica Sinica*, 2009, 35(6):650-667.
- [2] W.H. Gui, C.H. Yang, Y.G. Li, J.J. He, L.Z. Yin, Data-driven Operational-pattern Optimization for Copper Flash Smelting Process, *Acta Automatica Sinica*, 2009, 35(6):717-724.
- [3] L. Han, D.Y. Xiao, Survey on data driven fault diagnosis methods, *Control & Decision*, 2011, (1):1-9, 16
- [4] T.Y. Chai, Operational Optimization and Feedback Control for Complex Industrial Processes, *Acta Automatica Sinica*, 2013, 39(11):1744-1757.
- [5] Z.S. Wang, H.G. Zhang, J. Feng, S.X. Lun, Present Situation and Prospect on Leak Detection and Localization Techniques for Long-distance Fluid Transport-pipelines, *Control & Instruments in Chemical Industry*, 2003.
- [6] H.V.D. Silva, C.K. Morooka, I.R. Guilherme, T.C.D. Fonseca, J.R.P. Mendes, Leak detection in petroleum pipelines using a fuzzy system. *Journal of Petroleum Science and Engineering*, vol. 49, no. 3-4, pp. 223-238, 2005.
- [7] R. Isermann, Process fault detection based on modeling and estimation methods - a survey, *Automatica*, vol. 20, no. 4 pp. 387-404, 1984.
- [8] H. Ye, G. Wang, G. Fang, Application of wavelet transform to fault detection, *Acta Automatica Sinica*, 1997, 23.
- [9] J. Feng, H.G. Zhang, On-line computer detecting system of pipeline leak and its algorithm, *Control & Decision*, 2004, 19(4):377-382.
- [10] J.H. Liu, H.G. Zhang, J. Feng, On-Line Leak-Detection Method for Pressure Time Series of Oil Pipeline, *Journal of Northeastern University*, 2009, 30(3):321-324.
- [11] A. Lay-Ekuakille, P. Vergallo, G. Griffo, R. Morello, Pipeline flow measurement using real-time imaging, *Measurement*, 2014, 47(1):1008-1015.
- [12] J.H. Liu, J. Feng, Research on leak fault intelligent detection method for fluid pipeline based on fuzzy classification. *Chinese Journal of Scientific Instrument*, 2011, 32(1):26-32.
- [13] W. Liang, J. Kang, L. Zhang, Leak detection for long transportation pipeline using a state coupling analysis of pump units, *Journal of Loss Prevention in the Process Industries*, 2013, 26(4):586-593.
- [14] J. Hu, L. Zhang, W. Liang, Detection of small leakage from long transportation pipeline with complex noise, *Journal of Loss Prevention in the Process Industries*, 2011, 24(4):449-457.
- [15] D.L. Xu, J. Liu, et al, Inference and learning methodology of belief-rule-based expert system for pipeline leak detection, *Expert Systems with Applications*, vol. 32, no. 1, pp. 103-113, 2007.
- [16] J. Feng, D.Z. Ma, H.G. Zhang, Improved delay-dependent stabilization conditions of Takagi-Sugeno fuzzy systems with state and input delays, *Networking, Sensing and Control (ICNSC)*, 2010 International Conference on. IEEE, 2010:414-418.
- [17] H.G. Zhang, D.W. Gong, Z.S. Wang, D.Z. Ma, Synchronization Criteria for an Array of Neutral-Type Neural Networks with Hybrid Coupling: A Novel Analysis Approach, *Neural Processing Letters*, 2012, 35(1):29-45.
- [18] J.H. Liu, H.G. Zhang, J. Feng, Investigation of chaotic behavior for press time series of oil pipeline, *Acta Physica Sinica*, 2008, 57(11):6868-6877.
- [19] Q. Zhang, Dynamic uncertain causality graph for knowledge representation and reasoning: discrete DAG cases, *Journal of Computer Science and Technology*, 2012, 27(1): 1-23
- [20] C.L. Dong, Q. Zhang, Research on weighted logical inference for uncertain fault diagnosis, *Acta Automatica Sinica*, 2014, 40(12): 2766-2781.
- [21] Q. Zhang, C.L. Dong, Y. Cui, Z.H. Yang, Dynamic uncertain causality graph for knowledge representation and probabilistic reasoning: statistics base, matrix, and application. *IEEE Transactions on Neural Networks and Learning Systems*, 2014, 25(4): 645-663
- [22] J.H. Liu, Z.N. Wu, Y.X. Li, D.Y. Lu, Chaotic characters based oil pipeline leak detection method and system, *Intelligent Control and Automation (WCICA)*, 2014 11th World Congress on. IEEE, 2014.
- [23] J.H. Liu, J. Feng, D.Z. Ma, A High Accurate and Real Time Filter Method for Pressure Signal of Fluid Pipeline, *Journal of Northeastern University*, 2013, 34(1):9-12.
- [24] D.Z. Ma, H.G. Zhang, J. Feng, J.H. Liu, A fault diagnosis method based on multi-sensor information fusion, *Caai Transactions on Intelligent Systems*, 2009.
- [25] K.F. Wang, G.Z. Wang, et al, a method of leak diagnosis based on negative wave propagation in pipeline, *Information & Control*, 1992.