# Research on Adaptive Iterative Learning Control of Air Pressure in Railway Tunnel With IOTs Data

**YINJUN ZHANG**[1,2]**, JIANHUA SU**[1]**, AND MENGJI CHEN**[1]
[1]School of Physics and Electrical Engineering, Hechi University, Yizhou 546300, China
[2]School of Mechanical and Electrical Engineering, Guangxi Science and Technology Normal University, Laibin 546199, China

Corresponding author: Jianhua Su (18107786221@163.com)

**ABSTRACT** When a train enters a tunnel, the passengers in the train will feel tinnitus. The main reason is that the pressure in the tunnel enters the vehicle through the adjusting system of the train, which will cause discomfort to the passengers. In this paper, according to the quasi-periodicity and repeatability of mass data in the process of train running in tunnels, a control method based on the IOTs big data is proposed, and an adaptive iterative learning control algorithm based on the IOTs big data is established. The fan operation frequency of ventilation system is regulated by adaptive iterative learning control algorithm, and can adjust the new air and exhaust gas of the ventilation system in real time to restrain the pressure fluctuation in the train. Finally, the simulation results show that the adaptive iterative learning control algorithm based on the Internet of Things can significantly reduce the amplitude of pressure fluctuation in the tunnel and the change rate of the ventilator, and improve the passenger comfort program. Moreover, the real-time measured data also show that the proposed closed-loop adaptive iterative learning control algorithm based on the Internet of Things is obviously superior to active control.

**INDEX TERMS** Train in tunnel, pressure fluctuation, Internet of Things, adaptive iterative learning control.

## I. INTRODUCTION

When the train passes through the tunnel, the pressure in the tunnel will change very complex, thus forming the tunnel wave [1]–[2]. Tunnel waves enter the car through ventilation fans, train crevices, air-conditioning systems of trains, which can cause passengers' tinnitus, earache and other symptoms, thereby affecting passengers' comfort [3]–[4]. At present, there are two main ways to control the pressure fluctuation in the train, [5] active and passive. The working frequency of the active fan is constant, and the specific fluctuation of the tunnel wave is not fully considered. The passive mode is not suitable for use on multi-tunnel lines. Therefore, on the basis of the active control mode, a control mode is designed to adjust the running frequency of ventilator in real time according to the actual running state of the train, which can

The associate editor coordinating the review of this manuscript and approving it for publication was Patrick Hung.

effectively suppress the pressure fluctuation in the car and improve passenger comfort.

Aiming at the problem of air pressure fluctuation induced by train passing through tunnel, scholars at home and abroad have conducted in-depth research. Yuangui and Chaohui [6], Hao *et al.* [7], Shao Huanxia and other scholars have carried out numerical analysis on the pressure fluctuation inside the train when the train passes through the tunnel or meets the train in the tunnel, but most of them have analyzed and studied on a specific working condition, without considering the quasi-periodicity and repeatability of the train, so they need to adjust and adapt constantly in the train running. Based on the theory of Internet of Things, the tunnel pressure wave formed by train passing through the tunnel has quasi-periodicity and repeatability on a specific line. By using the non-linear mathematical model of air pressure transmission inside and outside the vehicle [9], combined with closed-loop adaptive iterative learning control, the Internet of Things

iterative learning control system is established to control the frequency of ventilator. In order to adjust the fresh air and waste discharge of the ventilation system in real time, the pressure fluctuation in the vehicle caused by the train passing through the tunnel can be controlled and simulated.

With the development of multi-sensor fusion technology, Internet of Things technology, cloud processing technology and electronic storage technology, the world has ushered in the era of "IOTs". IOTs method will become another scientific research method after theoretical analysis, simulation calculation and test method. In this paper, based on the theoretical deduction of the iterative learning algorithm, an iterative learning control algorithm based on the idea of large data is proposed for the multi-capacitive coupling process of the barometric simulation system. The algorithm is simulated and analyzed with the simulation model of the barometric simulation system.

## II. THE RELATIONSHIP BETWEEN INDOOR AND OUTDOOR AIR PRESSURE

The air pressure difference will occur when the train enters the tunnel. The function of the ventilator is to introduce fresh air and discharge the exhaust gas. According to the principle of conservation of mass, the air quality in the train at present is the sum of the air quality in the car at the last moment and the air quality in the car at the interval of time. In reference [9], the non-linear mathematical model of air pressure transmission inside and outside the vehicle is given, and the relationship between air pressure transmission inside and outside the vehicle when the train enters the tunnel is obtained by combining the actual situation of the train entering the tunnel.

$$
\begin{cases}
P_i(t) = P_i(t-1) + 0.0005(\frac{P_o(t-1)}{504000})(422 + 3.125 \\
\sqrt{18326 - 32(P_i(t-1)) - P_o(t-1) + 86400C_1}) \\
-\frac{P_o(t-1)}{504000}(420 + 20) \\
\overline{\sqrt{441 - 32(P_o(t-1)) - P_i(t-1) + 2100C_2}} \\
-\sqrt{0.005P_i^2(t-1) - P_o(t-1)P_i(t-1)}, \\
P_i(t-1) > P_o(t-1) \\
P_i(t) = P_i(t-1) + 0.0005(\frac{P_o(t-1)}{504000})(422 + 3.125 \\
\sqrt{18326 - 32(P_i(t-1)) - P_o(t-1) + 86400C_1}) \\
-\frac{P_o(t-1)}{504000}(420 + 20) \\
\overline{\sqrt{441 - 32(P_o(t-1)) - P_i(t-1) + 2100C_2}} \\
-\sqrt{0.005P_o^2(t-1) - P_o(t-1)P_i(t-1)}, \\
P_i(t-1) < P_o(t-1)
\end{cases} \tag{1}
$$

where $P_o(t)$ and $P_o(t-1)$ are external pressure at current and last moments, Unit is Pa; $P_i(t)$ and $P_i(t-1)$ are inner pressure at current and last moments, Unit is Pa;

## III. CONTROL STRATEGY DESIGN
### A. CONTROL ALGORITHMS SELECTION
After the train is put into operation on the same line, it will run at the same speed and under the same working condition
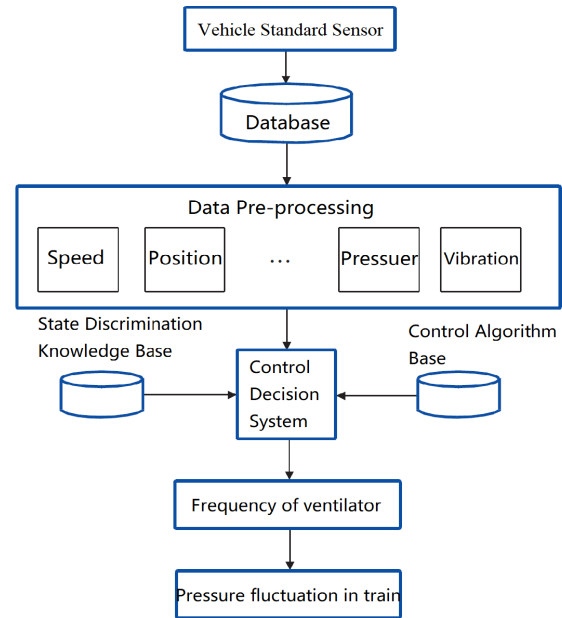


**FIGURE 1.** Block diagram of ventilator control system based on Internet of Things big data.

for a long time. In the process of repeated operation, the train generates a large amount of approximate repetitive data, including the running state, the pressure wave of the train meeting, the pressure wave of the tunnel, the vibration of the train and the comfort of the train, which can be called quasi-periodic data [10]. This paper mainly studies the suppression of the pressure fluctuation in the train by the frequency conversion of the ventilator when the train passes through the tunnel. Through the comparison and analysis of massive data, the frequency conversion control effect of the ventilator is obtained when passing through a specific tunnel, and the best working frequency of the ventilator is found to suppress the pressure fluctuation in the vehicle. Fig. 1 is a block diagram of ventilator control system based on IOTs big data.

$C_1 = (f_1/f_0)^2$ denotes speed regulation ratio of fresh air unit, $C_2 = (f_2/f_0)^2$ denotes speed regulation ratio of exhaust fan. $f_1$ and $f_2$ are working frequency of fresh air blower and exhaust air blower at current time respectively [9]. We set the initial working frequency is 30Hz.

We have tested the pressure of the tunnel outside the train when the train crosses the tunnel. Usually, the initial pressure inside the train is 15 Pa higher than that outside the train. According to the relationship between the air pressure inside and outside the train, by constantly adjusting the working frequency of the ventilator, we use Matlab software to simulate the fluctuation of the air pressure inside the train, and then compare and analyze the suppression of air pressure fluctuation in trains at different operating frequencies for ventilator.

From Fig. 1, we can know that the on-board standard sensor on the train can monitor the speed information, position information and pressure fluctuation information of the train in real time, and can judge whether the train passes through

the tunnel or not. When the sensor detects the train passing through the tunnel, the control decision-making system starts to work and calls the control algorithm library to control the working frequency of the ventilator, records and analyses the suppression of pressure fluctuation in the vehicle.

When the train enters the same tunnel under the same working condition again, it calculates and analyses the control results of the last time, and gives new control input according to the control rules, so as to continuously control and adjust until the control meets the requirements. Because of the quasi-periodicity and repeatability of the IOTs big data generated during the train operation. Among the existing control algorithms, Iterative Learning Control (ILC) is most suitable for handling systems with repetitive characteristics. Therefore, an Iterative Learning Control System for Vehicle Pressure Fluctuation is proposed based on the combination of IOTs big data and Iterative Learning Control (ILC).

## B. ITERATIVE LEARNING CONTROL ALGORITHM (ILC)

Iterative learning control was first proposed by Uchiyama in 1978, but because the paper was written in Japanese, the impact was not significant. In 1984, Arimoto [11], [12] and others introduced this method in English. It refers to the control method that repeats the same trajectory and modifies the control law to obtain very good control effect. At present, the research of iterative learning control (ILC) has become a hot topic [13]–[18].

Iterative learning control (ILC) is an important branch of learning control, and is a new learning control strategy. It obtains the desired output trajectory by repeatedly applying the information obtained from previous experiments to improve the control quality. Unlike traditional control methods, ILC can deal with dynamic systems with high uncertainties in a very simple way, and requires only a small amount of prior knowledge and computation, and has strong adaptability and is easy to implement; moreover, it does not depend on the exact mathematical model of dynamic systems, and is an iterative control method. An algorithm that optimizes the input signal and makes the output of the system as close as possible to the desired value. Its research is of great significance to those trajectory control problems with nonlinear, complex, difficult to model and high precision.

Iterative learning control (ILC) is very suitable for the controlled object with repetitive tasks. In limited control time, the current control is constantly revised according to the previous control experience of the control system, so that the actual output of the system is infinitely close to the expected output of the system [19], [20].

The ILC algorithm guarantees a uniform tracking performance when it is applied to the system iteratively. The main feature of this algorithm is that it requires less a priori knowledge about the controlled system dynamics in the controller design phase and uses the information about the past behavior of the system to generate the control input in the current iteration. The controller learns by remembering the effectiveness of the previous inputs and applies this knowledge

to improve the next input, hence, the learning mechanism is iteration. After each iteration, there should be no causality restriction, which means that one can use the information about the system response to the control input in constructing the control input.

The iterative learning control of continuous nonlinear systems has been studied by many scholars.

$$\begin{cases} x(t) = f(x(t)) + g(x(t))u(t) \\ y(t) = h(x(t)) + s(x(t))u(t) \end{cases} \quad (2)$$

When there is no input term in the output equation of system (2), the construction of system learning law requires the use of error derivatives. If the relative order of the system is r, then r-order error derivatives are needed. In order to prove the convergence of the learning system, we often assume that the nonlinear function f(.) and g(.) in system (2) must satisfy the Lipschitz global continuous condition. However, many nonlinear functions can only satisfy the local Lipschitz continuous conditions, so the convergence analysis of learning system can only be established in the local condition. At present, the main achievement of iterative learning control for nonlinear systems is to study the problem of trajectory tracking. In literature [21], the learning control strategy is applied to the state transfer control problem of nonlinear system successfully. The main way to solve the problem is based on the state feedback method. However, the algorithms need high requirements for the system in the literature [22]–[25], so it will be greatly restricted in practical applications.

We introduce adaptive control in the design of ILC, the controller can not only learn the prior knowledge of the system, but also deal with the non-linear uncertainties of the system with adaptive control, so as to optimize the dynamic response of the adaptive control process. So this paper uses adaptive ILC.

Iterative learning control corrects the unsatisfactory control signal by the deviation between the actual output signal and the expected signal of the system, which improves the tracking performance of the system. We define the tracking error of the system as

$$e_k(t) = y_d(t) - y_k(t) \quad (3)$$

The iterative learning law is composed of the current control information $u_k(t)$ and tracking error information $e_k(t)$, and we get the control information $u_{k+1}(t)$ of the next iteration.

$$u_{k+1}(t) = u_k(t) + L(e_k(t), t) \quad (4)$$

where $L$ is gain, and it is a linear function.

The control law and adaptive parameter learning law of the adaptive controller are as follows

$$u_k(t) = \dot{x}_k(t) + Le_k(t) + \hat{a}_k(t)x_k^2(t) \quad (5)$$

$$\begin{cases} \hat{a}_k(t) = \hat{a}_{k-1}(t) + L\phi_k(t)e_k(t) \\ \hat{a}_{-1}(0) = 0 \ \ t \in [0, T] \end{cases} \quad (6)$$

## C. INTERNET OF THINGS BIG DATA

Internet of Things (IOT) big data refers to real-time acquisition of any object or process that needs to be monitored, connected and interacted through various information sensors, radio frequency identification technology, global positioning system, infrared sensors, laser scanners and other devices and technologies, and acquisition of its sound, light, heat, electricity, mechanics, chemistry, biology, location and other needs. The necessary information can be accessed through various possible networks to realize the ubiquitous connection between things and people, and realize the intelligent perception, recognition and management of goods and processes. The IOTs big data is an information carrier based on the Internet, traditional telecommunication networks and so on. It enables all ordinary physical objects that can be independently addressed to form interconnected networks.

The IOTs big data is an extension and expansion of the Internet. It combines all kinds of information sensing devices with the Internet to form a huge network to realize the interconnection of people, machines and things at anytime, anywhere.

The Internet of Things big data is an important part of the new generation of information technology. The IT industry is also called pan-interconnection, which means that things are connected and everything is connected. Thus, "the Internet of Things is the Internet of Things''. This has two meanings: first, the core and foundation of the Internet of Things is still the Internet, which is an extension and expansion of the network on the basis of the Internet; second, its user end extends and extends to any goods and objects for information exchange and communication. Therefore, the definition of the Internet of Things is to connect any item to the Internet through radio frequency identification, infrared sensors, global positioning system, laser scanner and other information sensing devices, according to the agreed agreement, to exchange and communicate information, so as to realize the intelligent identification, location, tracking, monitoring and management of items. Species network [33]–[35].

There are five parts in this paper. The first part mainly introduces a research background. The third part mainly introduces some knowledge of Iterative Learning Control Strategy and Internet of Things. The fourth part mainly simulates and tests us. The fifth part summarizes the whole paper.

In this paper, we simulate and analyze the pressure inside and outside the vehicle passing through the tunnel. Because of quasi-periodicity and repeatability of the pressure fluctuation of the outside tunnel when the train passes through the tunnel on a specific line. In this paper, each time the train passes through the tunnel as an iterative control, according to the analysis and calculation of the suppression effect of the pressure fluctuation inside the vehicle when passing the tunnel last time, a new control quantity of fan working frequency is given according to the iterative learning law. By continuously iteratively controlling and adjusting the fan frequency of the ventilation system, the purpose of effectively suppressing the pressure fluctuation inside the vehicle is achieved.
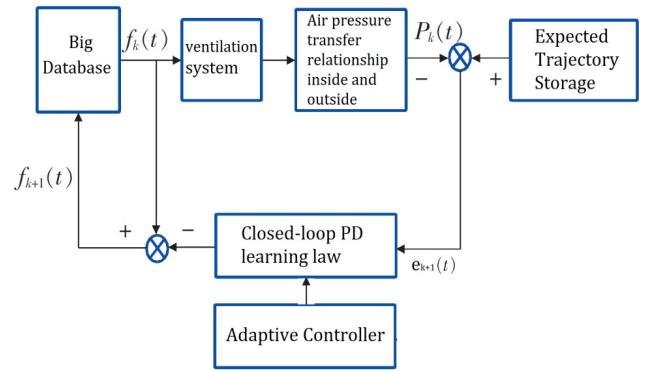


**FIGURE 2.** Simulation control model block diagram.

In this control system, the desired pressure fluctuation in the vehicle is $P_o(t)$, the pressure fluctuation in the vehicle is $P_i(t)$, k is iterative times (i.e. the k-th passage through the tunnel), so the tracking error of the system is

$$e_k(t) = p_o(t) - p_i(t) \tag{7}$$

In this paper, we choose closed-loop PD-type iterative learning control strategy:

$$f_{k+1}^1(t) = f_k^1(t) + L_p\phi_k(t)e_{k+1}(t) + L_d\phi_k(t)\dot{e}_{k+1}(t) \tag{8}$$

$$f_{k+1}^2(t) = f_k^2(t) + L_p\phi_k(t)e_{k+1}(t) + L_d\phi_k(t)\dot{e}_{k+1}(t) \tag{9}$$

where $f_k^1(t)$ and $f_{k+1}^1(t)$ are fan control frequency at the $k^{th}$ and $k+1^{th}$, $f_k^2(t)$ and $f_{k+1}^2(t)$ are exhaust fan control frequency at the $k^{th}$ and $k+1^{th}$, $L_p$ and $L_d$ are gain stationary matrices, $\phi_k$ is estimated value.

The simulation control model block diagram of air pressure in train is shown in Fig. 2.

About the convergence proof of adaptive iterative learning control, shown in [26]–[32].

## IV. SIMULATION ANALYSIS

Considering the actual operation of the train ventilator, in the simulation process, we set the frequency conversion control cycle $T_c = 4s$, the highest frequency $F_{max} = 40$ Hz, and the lowest frequency $F_{min} = 0.3$ Hz, which makes the frequency change in this range.

In this paper, we take a 150 *km/h* locomotive passing through a tunnel as an example, and use Matlab software for continuous iterative control. In the simulation, we set the expected value $P_0 = 0$ Pa of the pressure in the train, and take the pressure difference in the train as the iteration judgment condition. By continuously adjusting the adaptive gain matrix of PD learning law, the pressure difference in the train changes with the iteration number as shown in Figure 3.

From Fig. 3, we can see that the system has converged when the system iterates 20 times and completely when the system iterates 40 times. At this time, the air pressure deviation in the train is very small. At this time, the air pressure deviation in the vehicle is very small, only $e_{35} = 50.56$ Pa, which fully meets the comfort requirements of the passengers
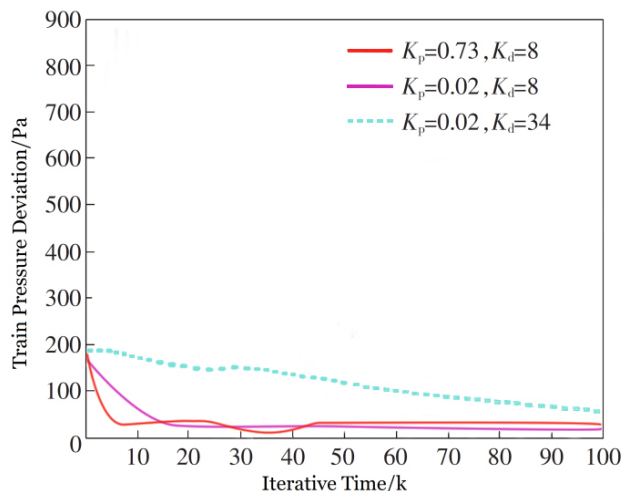
**FIGURE 3.** The VARIATION of pressure deviation in train with the number of iterations.

**TABLE 1.** Parameter table of pressure fluctuation in train head passing through tunnel.

| Control Way | Air pressure in train | | |
| --- | --- | --- | --- |
| | Volatility amplitude | Minimum change rate | Maximum change rate |
| Active Control | 773.23 | 102.48 | 291.57 |
| Iterative Control | 200.32 | 50.21 | 119.57 |
| Improvement rate/% | 73.98 | 51.93 | 58.39 |



**FIGURE 4.** Frequency variation curve of fan after 41st iteration.
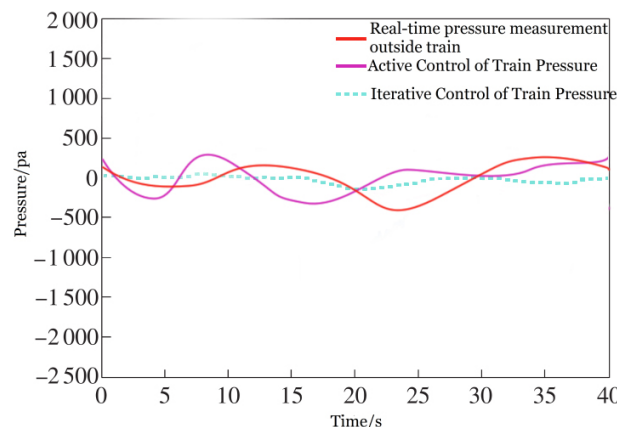


**FIGURE 5.** Contrast curve of iterative control and active control for head car passing through tunnel.

in the vehicle. Through continuous iteration control, the 40st iteration has converged completely, and the response time of the fan after the frequency change is not considered in the iteration control simulation. The frequency control method set in this paper is to control the air pressure value with sampling rate of 1 kHz point by point in 40 s Tunnel in each iteration process. It can be seen that the 41st iteration is the next. The frequency change curve of the fan is shown in Fig. 4.

The ventilation system is controlled by fan frequency in real time, and the pressure fluctuation in the vehicle is restrained continuously. After 41 iterations, the pressure fluctuation in the vehicle tends to the expected pressure fluctuation. When the head train passes through the tunnel, the simulation of the pressure fluctuation in the vehicle under the action of iterative control and active control is shown in Fig. 5. The comparison of the fluctuation amplitude, the maximum 1s change rate and the maximum 3s change rate is shown in Table 1. Fig. 5 shows that the pressure fluctuation in vehicle under iterative control is better than that under active control.

From Table 1, it can be seen that the fluctuation amplitude is reduced from 773.23 Pa to 200.32 Pa, the performance
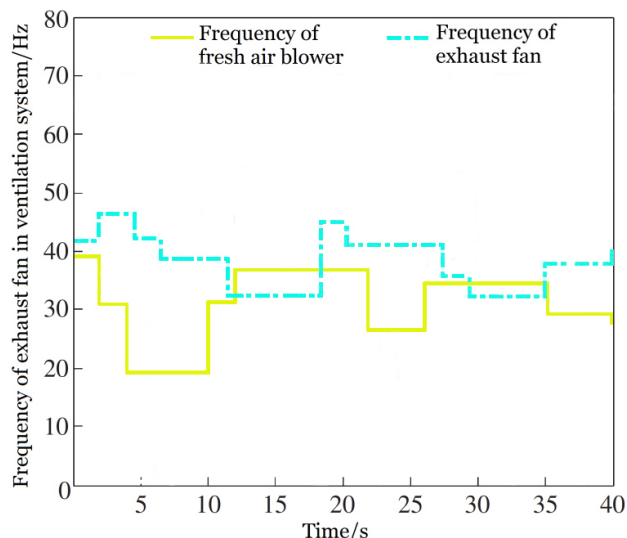
is improved by 74.09%, the maximum of 1 s change rate is reduced from 102.48 Pa to 50.21 Pa, the performance is improved by 51 %, and the maximum of 3 s change rate is also reduced from 291.57 Pa to 119.57 Pa. The performance was improved by 58.99%. It can be seen that the pressure fluctuation in the vehicle is more effectively restrained after the control mode of the ventilation system is changed to iterative control.

Similarly, the pressure fluctuation inside the train when the tail car passes through the tunnel is simulated and analyzed. The pressure fluctuation inside the train under the action of iterative control and active control is shown in Fig. 6, and the comparative parameters of the pressure fluctuation inside the train are shown in Table 2. It can be seen from the graph that the iterative control method is superior to the existing active control method when the train tail car passes through the tunnel. From Table 2, it can be seen that under the action of iterative control mode, the amplitude of in-car fluctuation decreased from 1011.79 Pa to 323.56 Pa,

**TABLE 2.** Parameter table of pressure fluctuation in train tail passing through tunnel.

| Control Way | Air pressure in train | | |
| --- | --- | --- | --- |
| | Volatility amplitude | Minimum change rate | Maximum change rate |
| Active Control | 1011.79 | 96.46 | 251.21 |
| Iterative Control | 323.56 | 70.21 | 158.74 |
| Improvement rate/% | 68.02 | 27.21 | 36.80 |
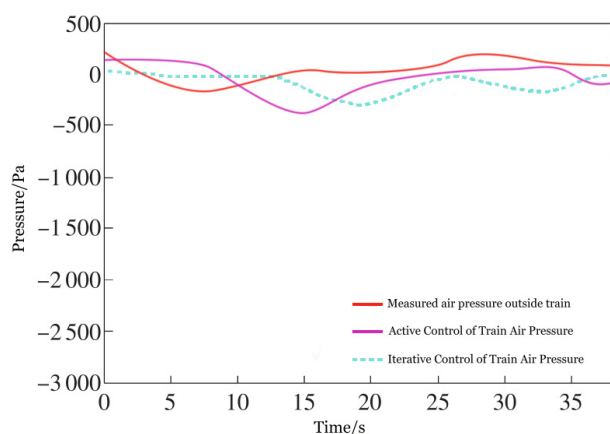


**FIGURE 6.** Contrast curve of iterative control and active control for train tail passing through tunnel.

the performance improved by 68.02%, the maximum 1 s change rate decreased from 96.46 Pa to 70.21 Pa, the performance improved by 27.21%, the maximum 3 s change rate decreased from 251.21 Pa to 158.74 Pa, and the performance improved by 36.80%. It can be seen that the pressure fluctuation in the vehicle can be more effectively suppressed after the control mode of the ventilation system is changed to iterative control.

## V. CONCLUSION

Based on the massive data of the Internet of Things, this paper uses the closed-loop adaptive PD iterative learning control algorithm to control the frequencies of the ventilator and exhaust fan in the train. From the simulation, we can see the superiority of the algorithm, and achieve the desired goal.

1) In this paper, a non-linear mathematical model of air pressure in train passing through a tunnel is used. Based on the massive data in the Internet of Things during the train repeat operation, an adaptive closed-loop PD-type iterative learning control algorithm based on the large data of the Internet of Things is proposed, and its mathematical simulation analysis is carried out.

2) For the established control system, the algorithm can real-time adjust the ventilator in the train based on the big data in the Internation of Things, that is, adjust the working

frequency of the ventilator, and then improve the comfort of passengers. The simulation analysis also shows that the proposed algorithm can not only adjust the working frequency of the ventilator, but also save energy.

## REFERENCES

[1] L. Renxian and Y. Lei, "Pressure fluctuation of high-speed train passing through tunnel," *J. Mech. Eng.*, vol. 50, no. 24, pp. 115–121, 2014.
[2] Y. Weifang, C. Chunjun, and D. Li, "Research on simulation control of pressure wave simulation system for high-speed train tunnel," *China Test*, vol. 40, no. 2, pp. 101–104, 2014.
[3] S. Haoming and G. Kuiyuan, "Research on tinnitus caused by pressure fluctuation in vehicle," *Foreign Railway Vehicles*, vol. 5, no. 5, pp. 15–18, 1999.
[4] C. Hu and W. Chuanhui, "Design of surface pressure test for high-speed train," *China Test*, vol. 38, no. 4, pp. 96–98, 2012.
[5] L. Shudian and Z. Xinxi, "Research on pressure fluctuation control of CRH2 200 km/h EMU," *Locomotive Electr. Drive*, vol. 2, no. 2, pp. 6–7, 2009.
[6] M. Yuangui and Z. Chaohui, "Numerical analysis of pressure fluctuation in carriage induced by high-speed train passing through tunnel," *J. Railway*, vol. 5, no. 5, pp. 36–40, 2005.
[7] D. Hao, L. Renxian, and L. Jie, "Analysis of the influence of ventilator on internal pressure fluctuation of high-speed train," *Mech. Eng. Autom.*, vol. 4, no. 4, pp. 1–3, 2013.
[8] S. Huanxia, M. Yuangui, and Z. Chaohui, "Preliminary study on numerical method of pressure wave in high-speed air-conditioned passenger car passing through tunnel," *Railway Locomotive Rolling Stock*, vol. 1, no. 1, pp. 31–33, 2006.
[9] X. Wenwei, C. Chunjun, and F. Chao, "Study on fuzzy control of pressure fluctuation in high-speed train," *Comput. Meas. Control*, vol. 9, no. 9, pp. 2781–2783, 2014.
[10] L. Guojie and C. Xueqi, "IOTs research: A major strategic field for the future development of science, technology and economic society—Research status and scientific thinking of IOTs," *J. Chin. Acad. Sci.*, vol. 6, no. 6, pp. 647–657, 2012.
[11] L. Renjun and H. Zhengzhi, "Overview of iterative learning control," *Control Decis.-Making*, vol. 9, no. 9, pp. 961–966, 2005.
[12] Y. Shaojuan, Q. Xiangdong, and W. Juhua, *Iterative Learning Control Theory and Application*. Beijing, China: Machinery Industry Press, 2005, pp. 76–92.
[13] M. Uchiyama, "Formation of high-speed motion pattern of mechanical arm by trial," *Trans. Soc. Instrum. Control Eng.*, vol. 14 no. 6, pp. 706–712, 1978.
[14] S. S. F. Arimoto, "Bettering operation of robots by learning," *J. Robotic Syst.*, vol. 1, no. 2, pp. 123–140, 1984.
[15] H. S. Ahn, C. H. Choi, and K. B. Kim, "Iterative learning control for a class of nonlinear system," *Automatica*, vol. 29, no. 6, pp. 1575–1578, 1993.
[16] P. Lucibello, S. Panzieri, and G. Ulivi, "Repositioning control of a two-link flexible arm by learning," *Automatica*, vol. 33, no. 4, pp. 579–590, 1997.
[17] H. Benslimane and A. Boulkroune, "Iterative learning control for strict-feedback nonlinear systems with both structured and unstructured uncertainties," *Arabian J. Sci. Eng.*, vol. 4, no. 9, pp. 3683–3694, 2016.
[18] T. Takagi and M. Sugeno, "Fuzzy identification of systems and its applications to modeling and control," *IEEE Trans. Syst., Man, Cybern.*, vol. SMC-15, no. 1, pp. 116–132, Jan./Feb. 1985.
[19] E. Kim and H. Lee, "New approaches to relaxed quadratic stability condition of fuzzy control system," *IEEE Trans Fuzzy Syst.*, vol. 8, no. 5, pp. 523–534, Oct. 2000.
[20] Y. Li and J. Li, "Stability analysis of fractional order systems based on T–S fuzzy model with the fractional order $\alpha : 0 < \alpha < 1$," *Nonlinear Dyn.*, vol. 78, no. 4, pp. 2019–2909, 2014.
[21] T. Taniguchi, K. Tanaka, and K. Yamafuji, "Nonlinear model following control via T-S fuzzy model," in *Proc. Amer. Control Conf.*, 1999, pp. 1837–1841.
[22] B. Sfaihi and M. Benrejeb, "On stability analysis of nonlinear discrete singularly perturbed T-S fuzzy models," *Int. J. Dyn. Control*, vol. 1, no. 1, pp. 20–31, 2013.
[23] M. Xiaojun and S. Zengqi, "Output tracking and regulation of nonlinear system based on Takagi–Sugeno fuzzy model," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 30, no. 1, pp. 47–59, Feb. 2000.
[24] H. Lee, J. Park, and Y. Joo, "Comments on 'Output tracking and regulation of nonlinear system based on Takagi–Sugeno fuzzy model'," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 33, no. 3, pp. 521–523, Jun. 2003.

[25] R. W. Longman, "Iterative learning control and repetitive control for engineering practice," *Int. J. Control*, vol. 73, no. 10, pp. 930–954, 2000.

[26] D. Shen and Y. Wang, "ILC for networked nonlinear systems with unknown control direction through random Lossy channel," *Syst. Control Lett.*, vol. 77, pp. 30–39, Mar. 2015.

[27] H. Liang *et al.*, "Discrete-time adaptive iterative learning control with incorporation of *a priori* process knowledge," *Trans. Inst. Meas. Control*, 2019, doi: 10.1177/0142331218810779.

[28] L. Hao, L. Na, C. Ronghu, and S. Yumei, "Discrete-time adaptive iterative learning control with incorporation of *a priori* process knowledge," *Trans. Inst. Meas. Control*, vol. 41, no. 11, pp. 1–12, 2019.

[29] H. Wu and J. Li, "Coordination control of uncertain topological high-order multi-agent systems: Distributed fuzzy adaptive iterative learning approach," *Soft Comput.*, vol. 23, no. 15, pp. 6183–6196, 2019.

[30] M. Benosman, A. Farahmand, and M. Xia, "Learning-based iterative modular adaptive control for nonlinear systems," *Int. J. Adapt. Control Signal Process.*, vol. 33, no. 2, pp. 225–227, 2019.

[31] X. Xing and J. Liu, "Modeling and robust adaptive iterative learning control of a vehicle-based flexible manipulator with uncertainties," *Int. J. Robust Nonlinear Control*, vol. 29, no. 8, pp. 1–21, 2019.

[32] B. Liang, F. Yun-Wen, L. Ning, and X. Xiao-Feng, "Robust model-free adaptive iterative learning control for vibration suppression based on evidential reasoning." *Micromachines*, vol. 10, no. 3, p. 196, 2019.

[33] X. Bu, S. Wang, Z. Hou, and W. Liu, "Model free adaptive iterative learning control for a class of nonlinear systems with randomly varying iteration lengths," *J. Franklin Inst.*, vol. 356, no. 5, pp. 2491–2504, 2019.

[34] X. Chen, "Talk about the Internet of Things," *Today's Sci. Park*, vol. 12, no. 20, pp. 54–59, 2011.

[35] M. R. Talaee, A. Kabiri, M. Ebrahimi, and B. Hakimzadeh, "Analysis of induced interior air flow in subway train cabin due to accelerating and decelerating," *Int. J. Ventilation*, vol. 18, no. 3, pp. 204–219, 2019.

[36] M. Khaleghi and M. R. Talaee, "Analysis of unsteady air flow in the subway station influenced by train movement," *Sci. Technol. Built Environ.*, vol. 1, pp. 1–10, Jun. 2019, doi: 10.1080/23744731.2019.1629244.

**YINJUN ZHANG** was born in Xinjiang, in 1984. He received the M.S. degree in control theory and control engineering from Guangxi Technology University, in 2011, and the Ph.D. degree from Air Force Engineering University. His research interests include fault diagnosis control and iterative learning control.

**JIANHUA SU** was born in Guangxi, in 1968. He received the M.S. degree from Chongqin University. He is currently a Professor with Hechi University. His research interests include single processing and nonlinear control.

**MENGJI CHEN** was born in Guangxi, in 1991. He received the bachelor's degree in automation from Hechi University, where he is currently pursuing the M.S. degree. His research interests include nonlinear control and data loss.

● ● ●