Data Driven State Monitoring of Maglev System With Experimental Analysis

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ABSTRACT The reliability of levitation system plays an important role for the safe operation of maglev train. Monitoring the state of the levitation system helps make early judgement to adopt fault tolerant measurement preventing further damage. In this paper, a data-driven state monitoring problem for PEMS high speed maglev train is studied in detail. Firstly preliminaries about levitation system and problem formulation are described. Then a residual generation method based on system input/output data is given. To tackle the varying operational condition problem, a multi-model switching strategy is proposed. For the non-Gaussian property of the system data, a Box-Cox transformation is adopted. The effectiveness of the proposed method is illustrated by experimental data analysis results.

INDEX TERMS High speed Maglev train, PEMS, Levitation system, data-driven, state monitoring.

I. INTRODUCTION

Maglev train is a new kind of railway transportation tool which features in the contact-less interact between train body and the track [1]. The advantages of maglev train include: strong climbing and turning ability, no danger of derailment, free of friction and wearing, and less environmental impact [2]. Levitation system, which is used for making the train body levitate above the track, is the key system for a maglev train [3]. To meet different application requirements, there has been a variety of maglev trains, among which permanent magnet electromagnetic suspension (PEMS) type maglev train is an innovative maglev aiming at energy-saving and long time levitation [4]. In PEMS maglev train, permanent magnet is added inside the iron core of the electromagnet, the size of the permanent magnet is optimized to reduce the levitation current and weight of the hybrid electromagnet [5]. Compared with traditional electromagnetic suspension (EMS) system, permanent magnet is added to reduce energy consumption. The subsequent advantage is the overheating phenomenon of the electromagnet is settled, which makes the PEMS system able to work 24-hour without a break. In this paper, PEMS high speed maglev train levitation system is the research object.

Since the opening of the first maglev train in Birmingham, UK in 1984 [6], researches about maglev trains have been widespread in countries like Japan [7], South Korea [8], Germany and China [9], [10]. The currently operational maglev trains include the Shanghai Maglev Train, Changsha Maglev Express, and Beijing maglev S1, etc. Take the Changsha Maglev Express as an examples, the maximum daily passenger flow reaches 15000. From operation experience, the maglev system needs to be maintained and repaired after a long time operation due to performance degradation and faults. The performance of the levitation system plays a key role in the riding comfort and safe operation. For commercial operational maglev train, the performances of levitation system degrades as time goes by. This degradation can be caused by the wearing and the aging of electrical components. For PEMS type maglev train, additional factors should be taken into consideration. The first case is the breakage of permanent magnet block caused by collision of hybrid electromagnet and the track. The second case is the demagnetization of permanent magnet. Both cases will cause the diminishing of magnetic force generated by the hybrid electromagnet, and further results in degradation of system performance. Finding a way to monitor the working status...
of maglev train in real time is a valuable and challenging task.

The researches on stability of railway transportation have been paid more attention these years [11]. The reliability of levitation system plays an important role for the safe operation of maglev train. Monitoring the state of the levitation system helps make early judgement to adopt fault tolerant measurement preventing further damages. Model based methods have been well developed in monitoring and evaluation of system performances [12]. However for maglev system, the model of levitation system is much too complicated for accurate acquisition, and the model can be time varying due to changing working condition. On the contrary, data can be acquired easily online, and these massive data have the potential to be used for precisely monitoring purpose [13]. A data-driven realization of kernel representations and their application to fault detection system are proposed in [14]. The system data can also be utilized to monitor the performance [15] and stability margin [16] of a control system, with the monitored performance index utilized in fault tolerant control [17]. The existing data-driven methods are usually applied to industry processes [18] which do not have high requirement on time response, and stable plants [19] which seldom consider stability requirement.

The following of this paper is organized as: In section II, preliminaries about levitation system and problem formulation are described. Then a residual generation method based on system input/output data is given in section III. Section IV is about the residual evaluation, including generation of test statistics and the set of the threshold. The effectiveness of this method is illustrated by experimental data analysis results in section V. Section VI concludes this paper with main results and future work prospect.

The notations used in this paper are standard. The \( n \)-dimensional Euclidean space is denoted as \( \mathbb{R}^n \), the set of all \( m \times n \) real matrix are denoted as \( \mathbb{R}^{m \times n} \), the superscript "\( T \)" stands for the transpose of a matrix, the superscript "\( -1 \)" is used for describing the inverse of a matrix.

II. PRELIMINARIES AND PROBLEM FORMULATION

In this part, some preliminaries about the maglev train levitation system principles and the characteristics of the system data are firstly described in detail. Then the main issues to be dealt with are given.

A. MATHEMATICAL MODEL OF MAGLEV SYSTEM

The structure of a single carriage of a high speed maglev train can be seen in the upper part of Figure 1. From levitation function point of view, maglev train can be divided into the upper half part of train body which is where passengers are, and lower half part of the levitation system which consists of air springs, electromagnets, arms and arm connectors. The air spring functions like a cushion offering better ride comfort. The electromagnets function like engines offering upward levitation force. The arms and arm connectors between electromagnets and air springs are used for connecting two adjacent electromagnets and transmitting the levitation forces. These two adjacent electromagnets, together with the arms and arm connectors compose a unit called a joint structure. There are 16 joint structures in a single carriage. With the decoupling mechanisms, the mutual influences between joint structures can be restricted to the minimum. Thus these joint structure levitation systems can be treated separatively as the fundamental levitation units.
1) FUNDAMENTAL EQUATIONS IN A MAGLEV SYSTEM
A fundamental levitation system is composed of electromagnet, sensors, controller and power amplifier. The model of a maglev system is composed of 3 parts: the relationship between voltage and current for an electromagnet, the relationship between magnetic force and current & levitation gap, and the dynamics of the electromagnet under load and magnetic force.

With parameters for PEMS maglev system defined in Table 1, the relationship of hybrid electromagnetic force \( F_{pe} \) with current \( i \) and levitation gap \( z \) is shown in (1):

\[
F_{pe} = \frac{\mu_0 S (2Ni + H_c z_m)^2}{(2z + z_m S/\mu_r S_m)^2} = \frac{\mu_0 N^2 S (i + H_c z_m / 2N)}{(z + z_m S/2\mu_r S_m)^2}
\]

\[
k_{pe} = \frac{\mu_0 N^2 S}{(z + \beta)^2} \tag{1}
\]

where \( k_{pe} = \frac{\mu_0 N^2 S}{(z + \beta)^2} \) and \( \alpha = H_c z_m / 2N, \beta = z_m S / 2\mu_r S_m \).

The relationship between voltage \( u \) and current \( i \) for a hybrid electromagnet can be described by:

\[
u = Ri + \frac{2\mu_0 N^2 S}{2z + z_m S/\mu_r S_m} \dot{z} - \frac{2\mu_0 NS (2Ni + H_c z_m)^2}{(2z + z_m S/\mu_r S_m)^2} \ddot{z} \tag{2}
\]

Under ideal condition the forces exerted on the electromagnet can be simplified as self gravity \( mg \), electromagnetic force \( F_{pe} \), and equivalent load \( Mg \). According to Newton’s second law, the dynamics of the electromagnet under load and magnetic force can be described by:

\[
m\ddot{z} = mg - F_{pe} + Mg
\]

\[
m\ddot{z} = mg - \frac{\mu_0 S (2Ni + H_c z_m)^2}{(2z + z_m S/\mu_r S_m)^2} + Mg \tag{3}
\]

For joint structure levitation system which consists of two electromagnets, the dynamics can be described by (4), with \( k_s(z_r - z_l) \) the coupling term generated by disc spring, \( k_s \) is related with the disc spring elastic coefficient. In (4), the subscript \( l \) and \( r \) refer to the variables belonging to the left and right side electromagnet respectively.

\[
\begin{align*}
m_l \ddot{z}_l &= mg - F_{pel} + M_l g + k_s(z_r - z_l) \\
m_r \ddot{z}_r &= m_r g - F_{per} + M_r g + k_s(z_l - z_r)
\end{align*} \tag{4}
\]

Under ideal condition, the levitation gaps within a joint structure is equivalent, i.e. \( z_r = z_l \). Considering system symmetry, system dynamics (4) can be simplified to (3) in the model analysis and controller design.

2) MODELS ANALYSIS FOR MAGLEV LEVITATION SYSTEM
The maglev system described by (1)-(3) is a nonlinear one. To analyze the system, first linearize the model in the adjacent of the equilibrium. Set the equilibrium gap as \( z_0 \) and \( x_1 = z, x_2 = \dot{z}, x_3 = i \), the equilibrium point for this maglev levitation system can be computed as:

\[
\begin{cases}
x_{10} = z_0 \\
x_{20} = 0 \\
x_{30} = i_0 = \sqrt{\frac{(M + m) g}{\mu_0 S}} \frac{2z_m S_m + z_m S}{2N} - \frac{H_c z_m}{2N}
\end{cases} \tag{5}
\]

A linearized model can be obtained as:

\[
\dot{x} = Ax + Bu \tag{6}
\]

\[
y = Cx + Du \tag{7}
\]

where

\[
a_{21} = \frac{4\mu_0 S (2Ni + H_c z_m)^2}{m(2z + z_m S/\mu_r S_m)^2}, \quad a_{23} = -\frac{4N \mu_0 S (2Ni + H_c z_m)}{m(2z + z_m S/\mu_r S_m)^2}, \quad a_{32} = \frac{2\mu_0 NS (2Ni + H_c z_m)^2}{2\mu_0 N^2 S}, \quad a_{33} = -\frac{R (2z + z_m S/\mu_r S_m)}{2\mu_0 N^2 S}
\]

Take the parameters for PEMS maglev system shown in Table 1, the eigenvalues of matrix \( A \) can be computed as \( \lambda_1 = -55.6365 + 48.0077i, \lambda_2 = -55.6365 - 48.0077i, \) and \( \lambda_3 = 48.5307. \) Since eigenvalue \( \lambda_3 \) is a positive real number, levitation system (6)-(7) is unstable.

3) CONTROL LAW DESIGN
With the design of a current loop [20], the voltage - current relationship of electromagnet (2) can be regarded as a proportional unit, i.e., \( u = i \) [21]. Then the system model (6) and (7) can be simplified as:

\[
\begin{bmatrix}
x_1 \\
x_2 \\
x_3
\end{bmatrix} =
\begin{bmatrix}
0 & 1 & 0 \\
0 & a_{21} & 0 \\
0 & a_{23} & a_{33}
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
x_3
\end{bmatrix} +
\begin{bmatrix}
0 \\
0 \\
b_3
\end{bmatrix}
u \tag{8}
\]

Now, since the system model of the levitation system has been obtained in the standard form of (9):

\[
\begin{bmatrix}
x(t) \\
y(t)
\end{bmatrix} = \begin{bmatrix}
x_1(t) \\
x_2(t) \\
x_3(t)
\end{bmatrix}, \quad u = \begin{bmatrix}
0 & 1 & 0 \\
0 & a_{21} & 0 \\
0 & a_{23} & a_{33}
\end{bmatrix}
\begin{bmatrix}
x_1(t) \\
x_2(t) \\
x_3(t)
\end{bmatrix} +
\begin{bmatrix}
0 \\
0 \\
b_3
\end{bmatrix}
u(t) \tag{9}
\]

classical linear quadratic optimal regulator (LQR) design method can be adopted to design the nominal controller [22].

Set the performance index as:

\[
J = \int_0^\infty (x^T W_x x + u^T W_u u) dt \tag{10}
\]

with \( W_x \) and \( W_u \) representing the weight on system state and control variable respectively, and solve the corresponding
FIGURE 2. Levitation gaps in fault-free condition.

FIGURE 3. Currents in fault-free condition.

Riccati equation:

\[ PA + A^T P - PB W u^{-1} B^T P + W_x = 0 \]  (11)

the nominal controller can be obtained as:

\[ u_c = -W_u^{-1} T P x \]  (12)

B. FAULT-FREE CONDITION EXPERIMENTAL DATA CHARACTERISTICS

To save the space, only the most representative data: levitation gaps and currents are displayed here. The levitation gaps for a joint structure levitation system can be seen in Figure 2, and the levitation currents for a joint structure levitation system can be seen in Figure 3. In the former 60 seconds the maglev train is under steady condition. There are small fluctuations in the gap and the current curves. In the latter 60 seconds, the maglev train is under running condition. The amplitude of the fluctuation becomes much larger. Specific statistics can be seen in Table 2 for levitation gap, in Table 3 for levitation current. The mean values of levitation gap and current under steady/running conditions are more or less the same. While the covariance of levitation gap and current under running conditions is much larger than those under steady condition.

C. PROBLEM FORMULATION

Based on the analysis made above, the main issues to be solved, which are also the main contributions of this paper, are summarized as:

- Though model based state monitoring methods are well studied in the past decade, for maglev train levitation system the complicated mechanical components and the unavoidable mutual influences between levitation systems, traction systems, and guidance systems make it difficult to acquire accurate system model. On the other hand, system input/output data are real reflection of system characteristics. The main task is to accomplish the monitoring task by utilizing system data without knowing the system characteristics. Meglev system is essentially a nonlinear, unstable system with high dynamics. Although some data-driven methods are developed, the applications to nonlinear unstable high dynamics system are rarely seen.

- Since the experimental data exhibit different statistical characteristics under different working conditions, like the velocities change in different line sections and the load capacities vary with passengers going on/off abroad, it is essential to discriminate these data accordingly. Besides, the experimental data is non-Gaussian, while according to classical method the threshold are set based on a Gaussian hypothesis. This non-Gaussian problem makes the monitoring result inconsistent with what is expected. How to process these experimental data to make the result more accurate becomes another issue to be tackled.

III. RESIDUAL GENERATOR IDENTIFICATION BASED ON SYSTEM DATA

A. DATA-DRIVEN DESCRIPTION FOR DYNAMIC SYSTEM

Firstly, notations for data driven description of dynamic system are introduced. Given a vector \( x(k) \in \mathcal{R}^n \), integers \( k_1, k_2 \) and \( N (k_1 < k_2) \), \( x(k) \) can be any variables in a control system,

| Conditions | Statistics | Values   | Units   |
|------------|------------|----------|---------|
| Steady     | mean       | 11.4419  | mm      |
|            | variance   | 0.0003   | mm²     |
| Run        | mean       | 11.1046  | mm      |
|            | variance   | 0.3736   | mm²     |
like input, output, noise, etc., then:

\[
X(k_1, k_2) = \begin{bmatrix} x(k_1) \\ x(k_1 + 1) \\ \vdots \\ x(k_2) \end{bmatrix} \in \mathcal{R}^{(k_2-k_1+1)s}
\]  

(13)

\[
X_N(k) = \begin{bmatrix} x(k) & x(k+1) & \ldots & x(k+N-1) \end{bmatrix} \in \mathcal{R}^{s \times N}
\]

(14)

\[
X_N(k_1, k_2) = \begin{bmatrix} \end{bmatrix}
 \begin{bmatrix} X(k_1, k_2) & X(k_1 + N - 1, k_2 + N - 1) \end{bmatrix} 
\]

\[
\in \mathcal{R}^{(k_2-k_1+1)s \times N}
\]

(15)

Given a discrete LTI control system described by:

\[
x(k+1) = Ax(k) + Bu(k)
\]

(16)

\[
y(k) =Cx(k) + Du(k)
\]

(17)

in which \( x(k) \in \mathcal{R}^n, y(k) \in \mathcal{R}^m, u(k) \in \mathcal{R}^l \). A data-driven form solution of (16) and (17) can be written as:

\[
y_N(k, k + s) = \Gamma(s)x_N(k) + H_u(s)U_N(k, k + s)
\]

(18)

where \( y_N(k, k + s) \in \mathcal{R}^{(s+1)m \times N}, X_N(k) \in \mathcal{R}^{n \times N}, U_N(k, k + s) \in \mathcal{R}^{(s+1)l \times N} \).

\[
\Gamma(s) = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^s \end{bmatrix} \in \mathcal{R}^{(s+1)m \times n}
\]

(19)

\[
H_u(s) = \begin{bmatrix} D & 0 & \ldots & 0 \\ CB & D & \ldots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ CA^sB & \ldots & CB & D \end{bmatrix} \in \mathcal{R}^{(s+1)m \times (s+1)l}
\]

(20)

Considering system noise \( w(k) \in \mathcal{R}^n \) and measurement noise \( v(k) \in \mathcal{R}^m \) (16) and (17) can be extended as:

\[
x(k+1) = Ax(k) + Bu(k) + w(k)
\]

(21)

\[
y(k) =Cx(k) + Du(k) + v(k)
\]

(22)

thus equation (18) can be further extended as:

\[
y_N(k, k + s) = \Gamma(s)x_N(k) + H_u(s)U_N(k, k + s)
\]

(23)

\[
+ H_w(s)W_N(k, k + s) + V_N(k, k + s)
\]

where

\[
H_w(s) = \begin{bmatrix} 0 & 0 & \ldots & 0 \\ C & 0 & \ldots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ CA^{s-1} & \ldots & C & 0 \end{bmatrix} \in \mathcal{R}^{(s+1)m \times (s+1)n}
\]

(24)

B. Parity Space Approach

A diagnosis observer (DO) is usually composed by a Luenberger type observer in the following form:

\[
x_o(k+1) = A_o x_o(k) + B_o u(k) + L_o r(k) \in \mathcal{R}^4
\]

(25)

\[
r(k) = G_y(k) - C_o x_o(k) - D_o u(k) \in \mathcal{R}
\]

(26)

where \( x_o(k) \) is an estimation of \( T_o x(k) \) with \( T_o \) the transformation matrix,

\[
T_o = A_o \Gamma_{s-1} = \begin{bmatrix} \alpha_{s,1} & \alpha_{s,2} & \ldots & \alpha_{s,s} & 0 \\ \vdots & \ddots & \ddots & \vdots & \vdots \\ \alpha_{s,s} & 0 & \ldots & 0 \end{bmatrix} \begin{bmatrix} A \\ CA \\ \vdots \\ CA^{s-1} \end{bmatrix}
\]

(27)

and the parameters \( A_o, B_o, L_o, G, C_o, \) and \( D_o \) solve the Luenberger conditions:

I. \( A_o \) is stable

II. \( T_o A - A_o T_o = L_o C, B_o = T_o B - L_o D \)

III. \( GC_o - C_o T_o = 0, D_o = GD \)

(29)

(30)

Comparing (28)-(30) with (16) and (17), the following relationships hold:

\[
A_o = T_o \alpha_{s-1} - L_o C
\]

(32)

\[
B_o = T_o B - L_o D
\]

(33)

\[
C_o = C \alpha_{s-1}
\]

(34)

\[
D_o = D
\]

(35)

Solving the Luenberger conditions (28)-(30) is a tough problem, while a mapping between parity space approach (PSA) and diagnosis observer is helpful in this design process. Suppose parity vector \( \alpha_s \) is known a prior, then the following mapping between observer (25)-(26) and parity vector can be used to construct observer [12]:

\[
A_o = \begin{bmatrix} 0 & 0 & \ldots & 0 \\ 1 & 0 & \ldots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \ldots & 1 & 0 \end{bmatrix}
\]

(32)

\[
B_o = \begin{bmatrix} D \\ CB \\ \vdots \\ CA^{s-1}B \end{bmatrix} = col(\alpha_s H_{u,s})
\]

(33)

Supposing \( \alpha_s H_{u,s} = [\beta_{s,0}^T \beta_{s,1}^T \cdots \beta_{s,s-1}^T]^T \), then

\[
B_o = \begin{bmatrix} \beta_{s,0} \\ \beta_{s,1} \\ \vdots \\ \beta_{s,s-1} \end{bmatrix}
\]

(34)

\[
D_o = \beta_{s,s}
\]

(35)
According to the mapping between DO and PSA, an observer can be designed based on parity space vector. If system matrix is known a priori, the observer can be constructed exactly according to this mapping. If the system model is unknown, then the following task is to identify parity space vector \( \alpha \), and the product \( \alpha_s H_{u,s} \). Then according to the relationship (32) to (38), this observer can be obtained.

### C. A Residual Generator Identification Approach

The procedure to identify the parity space vector \( \alpha \), and the product \( \alpha_s H_{u,s} \) using system data will be given in the following part. Equation (23) can be rewritten into a data driven I/O model as:

\[
\begin{bmatrix}
U_N(k, k + s) \\
Y_N(k, k + s)
\end{bmatrix} = \Psi(s) \begin{bmatrix}
U_N(k, k + s) \\
X_N(k)
\end{bmatrix} + \begin{bmatrix}
H_w(s)W_N(k, k + s) + V_N(k, k + s)
\end{bmatrix}
\]  

(39)

where

\[
\Psi(s) = \begin{bmatrix}
I \\
H_u(s)
\end{bmatrix} \in \mathbb{R}^{(s+1)(l+m) \times ((s+1)(l+n))}
\]  

(40)

Define data set as:

\[
Z_p = \begin{bmatrix}
U_N(k - s_p - 1, k - 1) \\
Y_N(k - s_p - 1, k - 1)
\end{bmatrix}
\]  

(41)

\[
Z_f = \begin{bmatrix}
U_N(k, k + s) \\
Y_N(k, k + s)
\end{bmatrix}
\]  

(42)

Through a QR factorization:

\[
\begin{bmatrix}
Z_p \\
U_N(k, k + s) \\
Y_N(k, k + s)
\end{bmatrix} = \begin{bmatrix}
R_{11} & 0 & 0 \\
R_{21} & R_{22} & 0 \\
R_{31} & R_{32} & R_{33}
\end{bmatrix} \begin{bmatrix}
Q_1 \\
Q_2 \\
Q_3
\end{bmatrix}
\]  

(43)

Then

\[
\begin{bmatrix}
U_N(k, k + s) \\
Y_N(k, k + s)
\end{bmatrix} = \begin{bmatrix}
R_{21} & R_{22} \\
R_{31} & R_{32}
\end{bmatrix} \begin{bmatrix}
Q_1 \\
Q_2
\end{bmatrix} + \begin{bmatrix}
0 \\
R_{33}Q_3
\end{bmatrix}
\]  

(44)

Then compared with (39), the following relationships can be obtained as [23]:

\[
\Psi(s) \begin{bmatrix}
U_N(k, k + s) \\
X_N(k)
\end{bmatrix} = \begin{bmatrix}
R_{21} & R_{22} \\
R_{31} & R_{32}
\end{bmatrix} \begin{bmatrix}
Q_1 \\
Q_2
\end{bmatrix}
\]  

(45)

\[
H_w(s)W_N(k, k + s) + V_N(k, k + s) = R_{33}Q_3
\]  

(46)

Multiply (45) by \( \Psi^\perp(s) = \begin{bmatrix} \Psi^\perp_u(s) & \Psi^\perp_y(s) \end{bmatrix} \). \( \Psi^\perp(s) \) belongs to the null space of \( \Psi(s) \), the following result can be obtained:

\[
\Psi^\perp(s) \begin{bmatrix}
R_{21} & R_{22} \\
R_{31} & R_{32}
\end{bmatrix} = 0
\]  

(47)

Then after a singular value decomposition (SVD),

\[
\begin{bmatrix}
R_{21} & R_{22} \\
R_{31} & R_{32}
\end{bmatrix} = \begin{bmatrix}
U_1 & U_2 \end{bmatrix} \begin{bmatrix}
\Sigma_1 & 0 \\
0 & \Sigma_2
\end{bmatrix} \begin{bmatrix}
V_1^T \\
V_2^T
\end{bmatrix}
\]  

(48)

with \( \Sigma_2 \approx 0 \), \( \Psi^\perp(s) \) can be chosen as \( V_2^T \). According to \( \Psi^\perp(s) \), \( \psi(s) = 0 \), the following two equations hold:

\[
\Psi^\perp_u(s) + \Psi^\perp_y(s)H_u(s) = 0
\]  

(49)

\[
\Psi^\perp_y(s)\Gamma(s) = 0
\]  

(50)

then the value of \( \alpha_\perp \) and \( \beta_\perp \) can be obtained as:

\[
\alpha_\perp = \Psi^\perp_y(s)
\]  

(51)

\[
\beta_\perp = \alpha_s H_u(s) = -\Psi^\perp_u(s)
\]  

(52)

Until now the identification of the observer based residual generator is completed, and this procedure can be summarized as:

- Collecting I/O data and making QR factorization (43);
- Making singular value decomposition (48), \( \Psi^\perp(s) \) chosen as \( U_2^T \);
- Obtaining \( \alpha_\perp \) and \( \beta_\perp \) according to (51) and (52);
- Constructing observer in the form of (25) and (26) according to (32) - (38).

### IV. Residual Evaluation

#### A. Normalization of System Data

This part gives a description about how to normalize the system data, which is also called preprocessing of system data. Given a system data set \( \mathcal{D} = \{ x(k) | x(k) \in \mathbb{R}^n, k = 1, 2, \ldots, N \} \), also \( x(k) \) can be any variables in a control system, like input, output, noise, etc.

The very first step is to get the mean value of the data as:

\[
\bar{x} = \begin{bmatrix}
x_1 \\
x_2 \\
\vdots \\
x_n
\end{bmatrix}, \quad \bar{x}_j = \frac{1}{N} \sum_{j=1}^{N} x_j (j)
\]  

(53)

and the standard deviation of the data as:

\[
\sigma = \begin{bmatrix}
\sigma_1 \\
\sigma_2 \\
\vdots \\
\sigma_n
\end{bmatrix}
\]  

(54)

where \( \sigma_j = \sqrt{\frac{1}{N-1} \sum_{j=1}^{N} (x_j (j) - \bar{x}_j)^2} \).

Then the normalized system data can be obtain as:

\[
\tilde{x} = \sigma^{-1} (x - \bar{x}_I_{1,N})
\]  

(55)

where \( I_{1,N} = [1 \ 1 \ \cdots \ 1] \in \mathbb{R}^{1 \times N} \).
B. GENERATION OF TEST STATISTICS

1) THE TRAINING STAGE
First get the residual $r$ with a residual generator in the form of (25) and (26), then calculate the covariance matrix of the sample data as:

$$
\Sigma = \frac{1}{N - 1} r r^T
$$

(56)

The test statistics for the training data can be generated as:

$$
T(x) = r^T \Sigma^{-1} r
$$

(57)

2) THE ONLINE MONITORING STAGE
A test sample $x_t$ is first obtained, the residual of the test sample is generated as $r_t$, then the test statistics is generated as:

$$
T(x_t) = r_t^T \Sigma^{-1} r_t
$$

(58)

C. BOX-COX TRANSFORMATION
The Box-Cox transforms non-normally distributed (non-Gaussian) data to a set of data that has approximately normal distribution [24]. For the test statistics obtained in (58), the transformed test statistics can be calculated in the following way:

$$
T_n(x_t) = \frac{T(x_t)^\lambda - 1}{\lambda}
$$

(59)

in which $\lambda$ is the transformation coefficient. This transformation makes $T_n$ approximate a normal distribution.

After the transformed test statistics $T_n$ is available, the mean value $\bar{m}$ and standard deviation $\sigma$ of $T_n$ can be obtained. Set the fault detection rate as 99.87%, the threshold can now be calculated as:

$$
Thr = \bar{m} + 3 * \sigma
$$

(60)

To conclude, the training procedure can be summarized as:
- Normalization of the training data following (53) - (55);
- Generation of residual with a residual generator in the form of (25) and (26), identification details given in (III-C);
- Generation of test statistics according to (56) and (57);
- Make a transformation according to (59) to get the transformed test statistics $T_n$;
- Obtain the mean value and standard deviation of $T_n$, then set a threshold accordingly like (60).

The online state monitoring procedure can be summarized as:
- Normalization of the test data $x_t$ following (53) - (55);
- Generation of the residual $r_t$;
- Generation of test statistics according to (56) and (58);
- Make a transformation according to (59) to get the transformed test statistics $T_n(x_t)$;
- Make a judgement about whether the system is fault or not based on the relationship between $T_n(x_t)$ and the threshold obtained in (60).

V. EXPERIMENT DATA ANALYSIS
In this part, an experiment is conducted on a high speed maglev train and the system input/output data is stored for further analysis. Figure 4 is the photo of a high speed maglev train at Shanghai Tongji high speed maglev test line. In the first stage the train is levitated above the track steadily without horizontal movement. In the second stage, the maglev train is tracted along the track slowly.

A. THE EFFECT OF THE BOX-COX TRANSFORMATION
The test statistics obtained from (58) do not have a normal distribution. To examine this, a normal probability plot of the test statistics is obtained, and the result can be seen in Figure 5. In this figure, each data is marked using plus sign (‘+’) markers and a reference lines which represent the theoretical distribution is exhibited. If the sample data has a normal distribution, then the data points appear along the reference line. As is seen in Figure 5, a curvature is introduced in the data plot, which implies the transformed data approximate a normal distribution, as is shown in Figure 6. These two figures
FIGURE 6. Norm probability plot of data after cox-box transformation.

TABLE 4. Statistics/Variables obtained from experiment data.

| Conditions | Statistics / Variable | Values      |
|------------|-----------------------|-------------|
| Steady     | mean                  | 3.6119      |
|            | standard deviation    | 0.1085      |
|            | \( \lambda_s \)       | -0.2544     |
|            | threshold              | 3.9382      |
| Run        | mean                  | 2.2064      |
|            | standard deviation    | 0.9548      |
|            | \( \lambda_r \)       | 0.0845      |
|            | threshold              | 5.0708      |

show the effectiveness of the Box-Cox transformation. The detailed statistics and variable values can be seen in Table 4. Denote the mean value under steady condition as \( \bar{m}_s \), under running condition as \( \bar{m}_r \); the standard deviation under steady condition as \( \sigma_s \), under running condition as \( \sigma_r \). With the fault detection rate of 99.87%, the threshold under steady / running condition can be set respectively as:

\[
Thr_s = \bar{m}_s + 3\sigma_s \tag{61}
\]

\[
Thr_r = \bar{m}_r + 3\sigma_r \tag{62}
\]

B. THE FINAL STATE MONITORING RESULT

A complete set of PEMS high speed maglev train joint structure levitation system data under fault-free and faulty condition, which consists of levitation gaps, currents within electromagnet windings, and voltages exerted on the electromagnets, are shown in Figure 7. The fault type in this figure is the current values become zero due to chopper fault alternatively on both sides of the joint structure levitation system for a duration time of 1 second.

To highlight the improved monitoring result of the proposed method, comparative results are give in Figure 8. In this result, the multi-model characteristic of the maglev train levitation system and the non-Gaussian property of the system data are not taken into account. For the multi-model characteristic, if the steady state threshold is adopted, then the running state data is more likely to be considered as a faulty data, which enlarges the false alarm rate (FAR); if the running state threshold is adopted, the fault happens in the steady state may not be detected in an early time, which reduce the fault detection rate (FDR). For the non-Gaussian property, a threshold set based on a Gaussian hypothesis makes the real FDR & FAR differ from what is expected.

To examine the effectiveness of the proposed method under faulty condition, a section of intermittent fault data under
running condition is taken as the test data. After the above mentioned procedures are conducted. A final state monitoring result can be obtained as shown in Figure 9. In this figure, the solid line is the test statistics while the dash line is the threshold. During the former 20 seconds the maglev train is under steady condition while during the latter 50 seconds the maglev train is under running condition. As mentioned before, two independent test statistics and thresholds are adopted for the two different working conditions. Under steady condition, the test statistics is below the threshold which implies the system is monitored as fault-free with no false alarm. Under running condition, in the first 30 seconds the test statistics is below the threshold which also implies the system is monitored as fault-free with no false alarm, while when the fault happens, the test statistics surpasses the threshold which implies the system is monitored as faulty. This state monitoring result is sensitive to the fault, with the fault detected in a short time with high accuracy.

VI. CONCLUSION

In this paper, a data-driven state monitoring problem for PEMS high speed maglev train is studied in detail. A residual generation method based on system input/output data is given, which is independent of the system model. To tackle the varying operational condition problem, a multimodel switching strategy is proposed. For the non-Gaussian property of the system data, a Box-Cox transformation is adopted. The effectiveness of this method is illustrated by experimental data analysis results. The proposed method has good prospects in future engineering practice: on one hand this method does not rely on system model, on the other hand the method is based on real levitation system data under different working conditions. In this paper steady and running conditions are treated separately. In real commercial operational line, levitation system models may change under different velocities and different working conditions like turning a curve and climbing a slope, which implies there are more working conditions. Training data and generating state monitoring related statistics based on more specific working conditions help improve the monitoring results. Engineering practice on a maglev line based on more detailed data is the future work focus.

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