Keywords: lift-preemptive-software; Fault detection; Fault prediction

Abstract

This paper presents an improved algorithm that can be used in the ‘lift-preemptive-software’ (LPS) developed in the NTU-JTC joint project. The improved algorithm successfully eliminated the ‘false alarms’ (defined later) generated by the old algorithm.

1 Introduction

Breakdown happens frequently to the cargo lifts in the industrial buildings. It costs a lot of money and manpower to repair the lift once it breaks down. Research has shown that most lift breakdowns are due to lift door failure. Therefore the ‘lift-preemptive-software’ (LPS) is designed to predict the lift door failure and send out alarms so that lift maintenance could be done before the lift actually breaks down.

The LPS has two parts, namely online software and offline analysis software. The online software is used to collect the real time data of the lift operation, process it using certain algorithm, analyze the result and determine whether to send out alarm. The offline analysis software is used to analyze all the data stored in the database and to assess the health condition of the lift. This paper just concentrates on the online software.

1.1 Parameters used in the LPS

The parameters used in the algorithms are listed as follows:

1) Door operation time $T_k$ (opening or closing):

The period during which the lift motor current $I_k$ is greater than a pre-defined threshold value.

2) Door operation energy $E_k$ (opening or closing)

The integration of the absolute value of the door motor current $I_k$ over the corresponding opening/closing time $T_i$, i.e.

$$E_k = \int_{T_i} |I_k| \, dt$$  \hspace{1cm} (1)

3) Door operation mean time $\bar{T}_k$

The average door operation time over the most recent $N$ door normal operations (defined later) at a particular storey, i.e.

$$\bar{T}_k = \frac{1}{N} \sum_{i=k-N}^{k-1} T_i$$  \hspace{1cm} (2)

where $N$ is the predefined data set size. Please note that only normal operation time is used to compute the mean value.

4) Door operation mean energy $\bar{E}_k$.

The average door operation energy over the most recent $N$ door normal operations at a particular storey, i.e.

$$\bar{E}_k = \frac{1}{N} \sum_{i=k-N}^{k-1} E_i$$  \hspace{1cm} (3)

Only normal operation energy is used to compute the mean value.

5) Door operation time deviation index $\alpha_k$.

The deviation of current door operation time from the mean value, i.e.

$$\alpha_k = \frac{T_k - \bar{T}_k}{\bar{T}_k}$$  \hspace{1cm} (4)

6) Door operation energy deviation index $\beta_k$.

The deviation of current door operation energy from the mean value, i.e.

$$\beta_k = \frac{E_k - \bar{E}_k}{\bar{E}_k}$$  \hspace{1cm} (5)

7) Standard deviation of door operation mean time $\sigma_{T,k}$.

It is defined as follows:

$$\sigma_{T,k} = \sqrt{\frac{1}{N} \sum_{i=0}^{k-1} (T_{k-i} - \bar{T}_{k-i})^2} / \bar{T}_{k-i}$$  \hspace{1cm} (6)

where $N$ is the sample size.

8) Standard deviation of door operation mean energy $\sigma_{E,k}$.

It is defined as follows:

$$\sigma_{E,k} = \sqrt{\frac{1}{N} \sum_{i=0}^{k-1} (E_{k-i} - \bar{E}_{k-i})^2} / \bar{E}_{k-i}$$  \hspace{1cm} (7)
where $N$ is the sample size.

9) *Abnormal door operation index* $\gamma$.

$$\gamma = \frac{N_{\text{abnormal}}}{N_{\text{total}}} \times 100\%$$  

(8)

where $N_{\text{total}}$ is the number (=20 in this paper) of most recent door operations (normal and abnormal) at a particular storey, $N_{\text{abnormal}}$ is the number of abnormal operations at a particular storey among the $N_{\text{total}}$ most recent door operations.

10) *Abnormal car/landing door operation index* $\lambda$.

$$\lambda = \frac{N_{\text{abnormal}}}{N_{\text{total}}} \times 100\%$$  

(9)

where $N_{\text{abnormal}}$ is defined in the 9), $N_{\text{total}}$ is the total number of abnormal door operations within the time interval defined by $N_{\text{total}}$.

### 1.2 The LPS algorithm

Based on the parameters introduced earlier, the algorithm of the LPS online software is as follows:

1. Collect lift operating time $T_k$ and motor current $I_k$ from the DAQ cards.
2. Calculate $E_k$, $T_k$, $E_k$ using formulas (1),(2) and (3) (assume there are enough data stored in the database.)
3. Calculate $\alpha_k$, $\beta_k$, $\sigma_{T,k}$, $\sigma_{E,k}$ using formulas (4), (5), (6) and (7).
4. Determine whether current operation is a normal operation or an abnormal operation.

*Note: Unless specified, door operations always refer to either closing or opening.*

**Door abnormality:**

According to Gaussian distribution,

- if $\alpha_k > 3 \sigma_{T,k}$ and $\beta_k > 3 \sigma_{E,k}$, save the current data into abnormal door operation database.
- else save the current data into normal door operation database.

5. Calculate $\gamma$, $\lambda$ using formulas (8) and (9) and determine whether to alarm.

For example, assume currently the operation is at storey $L_i$ and the computer time is $t_i$

1) go into the **normal door** operation database of level $L_i$ to find $t_2$ so that there are 20 normal door operations within this $(t_2, t_1)$.
2) go into the **abnormal door** operation database to find the number of abnormal door operation data of level $L_i$ within $(t_2, t_1)$, let’s say $n$.
3) combine these $20+n$ operations found in 1) and 2), and sort them by computer time.
4) starting from $t_1$, find $t_i$ so that there are 20 door operations (normal and abnormal) within the time interval $(t_i, t_1)$.
5) go into the **abnormal door** operation database to find the number of abnormal door operation data of level $L_i$ within $(t_i, t_1)$, i.e $N_{\text{abnormal}}$ defined in 9) of section 1.1.
6) calculate $\gamma$ using formula (8), where $N_{\text{total}}=20$ in this case.
7) go into the **abnormal door** operation database to find the number of abnormal door operations of all floors within $(t_1, t_i)$, i.e $N_{\text{abnormal}}$ defined in 9) of section 1.1.
8) calculate $\lambda$ using formula (9).
9) if $\gamma < 0.80$ (threshold value of $\gamma$), no alarm.

- else if $\lambda \geq 0.80$, this is a car door alarm.
- else $\lambda < 0.80$, this is a landing door alarm.

10) the alarm signal will last for 10 seconds. If there are more than one alarms generated in one day, only the first and the fifteenth will be sent out.

### 2 Problems with the Existing Algorithm

Four lifts (C,D,F,G) located at two different locations (site A and B) have been monitored by the LPS. During the monitoring, some alarms were sent out by the LPS; some fault simulations and breakdown were recorded by the company. The details are listed in Tables 1 and 2:

<table>
<thead>
<tr>
<th>Month</th>
<th>Alarm Time</th>
<th>Lift</th>
<th>Alarms sent out</th>
<th>Events</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oct. 01</td>
<td>08/10/2001, 21:11</td>
<td>F</td>
<td>Level 1 landing door.</td>
<td>False alarm</td>
</tr>
<tr>
<td></td>
<td>22/10/2001, 06:39</td>
<td>F</td>
<td>Level 1 landing door.</td>
<td>False alarm</td>
</tr>
<tr>
<td>Nov. 01</td>
<td>22/11/2001, 04:43</td>
<td>F</td>
<td>Level 1 landing door.</td>
<td>False alarm</td>
</tr>
</tbody>
</table>

Table 1: Table 3: Alarms sent out at Site B
Comparing the records with the alarms sent out, the following problem is discovered:

Although the LPS was capable of predicting lift door faults before the lift breakdown, it is too sensitive. Many alarms were sent out, however there was no actual lift breakdown later (we may call these alarms ‘false alarms’). For example: there were 18 alarms sent out for lift D at site A during 18/June/02—27/June/02; but from Table 2, there was actually no breakdown happened to lift D. Thus these 18 alarms are called ‘false alarms’. This problem may cause a lot of confusions if unsolved.

### 3 Improvements

#### 3.1 Calculate $\gamma$ for door closing and door opening separately

Since the value of $\gamma$ is critical in determining whether to alarm, we may need to examine it in details. \textit{(note: the accuracy of distinguishing car door fault and landing door fault is very good already, thus $\lambda$ is not discussed in this paper.)} As stated in section 1.2, the $N_{\text{total}}$ operations include both closing and opening. But it is common that the door closing and door opening can behave quite differently even for the same lift door. For example, the door closing and opening time for site A lift C during June/02—Aug/02 are shown in Figures 1 and 2.

<table>
<thead>
<tr>
<th>Month</th>
<th>Alarm Time</th>
<th>Lift</th>
<th>Alarms sent out</th>
<th>Events</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dec. 01</td>
<td>20/12/20 01:14:15</td>
<td>C</td>
<td>Car door.</td>
<td>Fault simulation with sand.</td>
</tr>
<tr>
<td></td>
<td>30/12/20 01:13:57</td>
<td>D</td>
<td>Level 4 landing door.</td>
<td>False alarm</td>
</tr>
<tr>
<td></td>
<td>31/12/20 01:00:02</td>
<td>D</td>
<td>Level 4 landing door.</td>
<td>False alarm</td>
</tr>
<tr>
<td></td>
<td>07/01/20 02:15:41</td>
<td>D</td>
<td>Level 1 landing door.</td>
<td>False alarm</td>
</tr>
<tr>
<td></td>
<td>07/01/20 02:16:08</td>
<td>D</td>
<td>Level 1 landing door.</td>
<td>False alarm</td>
</tr>
<tr>
<td></td>
<td>08/01/20 02:05:33</td>
<td>D</td>
<td>Level 1 landing door.</td>
<td>False alarm</td>
</tr>
<tr>
<td></td>
<td>10/01/20 02:15:15</td>
<td>C</td>
<td>Level 5 landing door.</td>
<td>Fault simulation with door shoes.</td>
</tr>
<tr>
<td>June 02</td>
<td>10/06/20 02:21:50</td>
<td>C</td>
<td>Level 7 landing door.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>11/06/20 02:04:17</td>
<td>C</td>
<td>Level 7 landing door.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>11/06/20 02:08:34</td>
<td>C</td>
<td>Level 7 landing door.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>18/06/20 02:17:34</td>
<td>D</td>
<td>18 alarms of Level 1 landing door.</td>
<td>False alarms</td>
</tr>
<tr>
<td></td>
<td>27/06/20 02:08:01</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Alarms sent out at site A

In Figures 1 and 2, the vertical axis represents the operation time (seconds) while the horizontal axis represents the operation series number. It can be seen that the door closing time and opening time differs from each other in both the average value and the fluctuations of the plot. Sometimes they even change in opposite direction, e.g. the parts around point 350 in both figures (from the database, they both correspond to the operations in 11/June/02). Due to this difference, the door mean operation time will be different for door closing and opening. Consequently the criteria of differentiating normal and abnormal operations will be different. Therefore it is better to calculate $\gamma$ for door closing and opening separately.

#### 3.2 Adjust the sample size and threshold deviation

Since the LPS uses Gaussian distribution probability model to differentiate normal and abnormal operations, it may be useful to adjust some of the parameters in this model. Obviously, for different sets of parameters, we can get different sets of normal and abnormal operations, consequently different sets of the $\gamma$ value and alarms sent out. The Gaussian distribution probability model is shown in Figure 3, where $z$ is defined in formula (10)

$$z = \frac{y - \mu}{\sigma} \quad (10)$$

In the LPS, $y$ corresponds to $T_{\text{k}}$, $\mu$ corresponds to $\bar{T}_{\text{k}}$, $\sigma$ corresponds to $\sigma_T$ and $z = 3$(threshold deviation factor).

The sample size used for site A is 100 and 50 for site B. $T_{\text{k}}$,
\( \bar{T}_k \) and \( \sigma_T \) are varying all the time, therefore parameters can be adjusted are the sample size and the value of \( z \).

Figure 3: Standard Gaussian Distribution Curve

To solve the problem of too many ‘false alarms’, we can do two things: increase the sample size or increase the value of \( z \). But the probability for \( z > 3 \) is very low already (0.0013 according to the normal distribution table), it will not affect the result a lot even for a higher \( z \). Therefore we need to increase the sample size. By trial and error, it is found that 200 is a much more appropriate sample size than 100 and 50. The drawback of this adjustment is too few abnormal operations will be detected, i.e. the new algorithm is too stringent. Therefore, \( z \) is adjusted to 2 to eliminate this drawback. The probability of \( z > 2 \) is 0.0227, which means there will be more abnormal operations.

3.3 Simplify the algorithm of calculating \( \gamma \)

Examining steps 3) to 6) in the algorithm of calculating \( \gamma \) in point 5 of section 1.2 carefully, we can find that the algorithm still works very well without steps 4) and 5). The value of \( \gamma \) can be calculated just using formula (11) with all the other parameters unchanged.

\[
\gamma = \frac{n}{20 + n} \times 100\% \tag{11}
\]

To make it clear, the simplified algorithm is illustrated as follows:

Assume currently the operation is at storey \( L_i \) and the computer time is \( t_1 \)

1) go into the normal door operation database of level \( L_i \) to find \( t_2 \) so that there are 20 normal door operations within this \((t_2, t_1)\).
2) go into the abnormal door operation database to find the number of abnormal door operations of level \( L_i \) within \((t_2, t_1)\), let’s say \( n \).
3) calculate \( \gamma \) using formula (11).

By rewriting formula (11) as formula (12), we can see \( \gamma \) increases with \( n \).

\[
\gamma = \frac{1}{1 + 20 / n} \times 100\% \tag{12}
\]

Thus by setting a proper threshold value for \( \gamma \), the new algorithm can successfully predict lift faults. By trial and error, the threshold \( \gamma \) is set at 50%.

Combine the three improvements discussed in 3.1—3.3, we can now re-process the raw operation data to see the effect. The result shows that only one alarm was sent out at 7:47 on 11/June/02 for storey 7 of lift C at site A (From the company’s records, door arm spring at storey 7 came off at 13:09 on the same day to the same lift). All the ‘false alarms’ listed in Tables 1 and 2 have been removed successfully.

However, it is worth noting that no alarm was raised for all the fault simulations conducted. This is because that the simulations did not last long enough and the value of \( \gamma \) had not exceeded the threshold value when the simulations stopped. However the algorithm did detect the abnormality. This is illustrated by Figures 4 and 5:

Note: \( \gamma \) is calculated only for abnormal operations, that’s why there are so few points in Figures 4—5.

In Figures 4—5, the vertical axis represents the value of \( \gamma \) (percents) while the horizontal axis represents the operation’s series number. The horizontal red line represents the threshold value.

It can be seen that the value of \( \gamma \) is increasing for both figures. Take Figure 4 as an example, points 7--17 correspond to the period of 10:23—11:10 on 20/Dec/01 when the fault simulation with door shoe was carried out. Therefore we are quite confident to say that if the fault simulation lasted longer, the value of \( \gamma \) would keep increasing and exceed the threshold value at some time later.

Therefore we can conclude that the improvements made are successful.
5. CONCLUSIONS

During this UROP, many ways for improving the accuracy of the LPS were tried out. Finally, three improvements were successfully added to the existing algorithm: calculate $\gamma$ for door closing and door opening separately; adjust the sample size and threshold deviation and simplify the algorithm of calculating $\gamma$. The improvements were verified based on the existing data.

6. ACKNOWLEDGMENT

The authors would like to acknowledge Dr Zhu Xing for his generous support and precious advice.

7. REFERENCE