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Development of a subway operation incident delay model using accelerated failure time approaches

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ABSTRACT

This study aims to develop a subway operational incident delay model using the parametric accelerated time failure (AFT) approach. Six parametric AFT models including the log-logistic, lognormal and Weibull models, with fixed and random parameters are built based on the Hong Kong subway operation incident data from 2005 to 2012, respectively. In addition, the Weibull model with gamma heterogeneity is also considered to compare the model performance. The goodness-of-fit test results show that the log-logistic AFT model with random parameters is most suitable for estimating the subway incident delay. First, the results show that a longer subway operation incident delay is highly correlated with the following factors: power cable failure, signal cable failure, turnout communication disruption and crashes involving a casualty. Vehicle failure makes the least impact on the increment of subway operation incident delay. According to these results, several possible measures, such as the use of short-distance and wireless communication technology (e.g., Wifi and Zigbee) are suggested to shorten the delay caused by subway operation incidents. Finally, the temporal transferability test results show that the developed log-logistic AFT model with random parameters is stable over time.

1. Introduction

The subway is an efficient, low carbon emission and safe transportation mode, and it also plays a vital role in the urban public transportation service. Subway operation incidents could cause great disruption to passengers, despite the low likelihood of occurrence. Hereafter, a subway operation incident is defined as an event related to the breakdown of subway operation caused by system component failures (e.g., power failure). Travel delays resulting from a subway operation incident are the major consequence concerning passengers; travel delays are measured by the difference between the scheduled and actual subway vehicle departure times. Therefore, public transportation authorities have to implement effective management strategies with the objective of clearing subway incidents as quickly as possible. Clearing a subway incident requires a quick and efficient allocation of resources that are needed to dispatch the crew in a timely manner. This response can be achieved through a comprehensive understanding of the factors affecting incident delays, and the appropriate use of predicted incident delay information (Chung, 2010). Information on predicted incident delays could alert passengers of the necessity to reschedule their trips.

A number of studies have focused on the analysis of subway operation incidents, and the resulting economic and human life loss. For example, fire is one disaster that can affect an underground subway system. Using historical subway fire accident records, Cheng et al. (2001) analyzed the major causes of fire accidents and put forward suggestions to reduce the corresponding occurrence likelihood. In addition, several other studies analyzed the major cause of precipitation (Quan et al., 2011), terrorist attacks (Staten, 1997; Okumura et al., 2005) and drivers' mental state (Mishara, 1999). However, these studies only addressed the major factors leading to subway incidents based on the particular type of incident. According to He et al. (2005), subway incidents could be induced by failures of the power system, subway vehicles, ventilation and smoke exhaust systems, water supply and drainage system, communication and signaling system, etc.

To provide reliable traffic information and to improve travel time reliability, there is a need to conduct a comprehensive analysis of subway incident delays (Lyman and Bertini, 2008). Thus far, a number of models, such as the accelerated failure time (AFT) models (Chung, 2010; Tavassoli et al., 2013), artificial neural network models (Wei and Lee, 2007), Bayesian methods (Cox and Snell, 1968; Greene, 2002; Kleinbaum, 1998; Ma et al., 2008) and so

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on, have been developed to predict freeway incident duration and have proposed effective countermeasures to mitigate congestion and accident risk. Compared to various studies on freeway incident duration, the studies on subway operation incident delay are rather limited. In reality, it is of great importance for public transportation authorities to take effective strategies to mitigate negative consequences (i.e., delay for passengers) caused by subway incidents, especially in super large-sized cities with huge public travel demands.

2. Literature review

Many researchers have focused their attention on subway incidents, such as fire (Cheng et al., 2001), precipitation (Bertness, 1980; Quan et al., 2011), terrorist attacks (Staten, 1997; Policastro and Gordon, 1999; Okumura et al., 2005), suicide (Mishara, 1999), etc. Lin and Gill (2009) examined the characteristics of subway train-related fatalities, between January 2003 and May 2007 in New York City. They concluded that passengers' behavior influenced by antidepressant medications, cocaine and alcohol were more frequent in suicide accidents. Chow et al. (2004) reviewed incidents in the past 32 years, and explored the causes of incidents related to fire and inadequate ventilation due to system faults, power failure, signal fault and temporary malfunctions of the platform screen doors. According to the Department of Transportation (DOT, 2000), it was found that incidents at highway-rail crossings (including trespassing) caused 93.8% of the deaths and 12% of the injuries in rail operations in the past five years. In conclusion, influencing factors such as passengers' behavior, system faults, power failure, signal faults, platform screen doors and synoptic factors should be considered in subway risk management.

The above-mentioned studies were only concerned with particular types of subway operation incidents. However, the analysis of a particular incident type is insufficient because there are various possible types of incidents in reality, and the delays caused by different types of incidents are uniquely different. In addition, the occurrence of subway incidents may be caused by multivariate factors. He et al. (2005), by analyzing the accident records globally in recent years, noted that subway incidents could be caused by failures of the power system, vehicle, ventilation and smoke exhaust system, water supply and drainage system, communication and signaling system. Many other factors, such as external crashes, mechanical failure and the mental state of drivers, were also found to induce subway operation incidents (Yeo et al., 2006). Therefore, a multivariate approach is more appropriate in the analysis of subway operation incidents.

Thus far, a number of multivariate approaches have been proposed for risk assessment (Valenti et al., 2010) and have been available for the analysis of subway operation incidents. These approaches can generally be divided into two groups: (i) qualitative assessment approaches and (ii) quantitative assessment approaches. Among the qualitative approaches, AHP is a typical method for the identification of potential hazards during a subway operation period. The Delphi method is often used with fault tree analysis by assuming the probability and the consequence of a specific incident type (Hong et al., 2009). Nevertheless the qualitative assessment approaches depend highly on the experts' subjective judgment, which may lead to significant estimated errors. Compared with qualitative assessment methods, quantitative methods produce more reliable results because of the avoidance of subjective judgment errors by using objective historical data.

The commonly utilized quantitative analysis methods with respect to incident duration can be categorized into (1) probabilistic distribution analysis (Giuliano, 1989; Chung, 2010); (2) time sequential methods (Khattak et al., 1995); (3) Bayesian methods (Ma et al., 2008; Kim and Chang, 2012); (4) fuzzy logic models (Kim and Choi, 2001); (5) artificial neural networks (Wang et al., 2005; Wei and Lee, 2007); (6) linear regression analyses (Valenti et al., 2010); (7) non-parametric regression methods and tree-style classification models (Smith and Smith, 2001; Ma et al., 2008); and (8) hazard-based models (Nam and Mannering, 2000; Tavassoli et al., 2013). Among the above multivariate approaches, parametric accelerated failure time approaches are the most commonly used in modeling time-related variables.

Although a number of multivariate models have been developed for freeway/highway incidents, there are a very limited number of models for subway operation incidents. In addition, although delays are the major concern of passengers, there are few studies focusing on the analysis of subway operation incident delays. In view of these limitations, a multivariate parametric model should be developed to estimate the subway operation incident delay and to explore the influencing factors of incident delays.

3. Objectives and contributions

The objective of this study is to develop a subway operation delay estimation model using the parametric accelerated failure time approach. To achieve this objective, the Hong Kong subway operation incident data from 2005 to 2011 will first be utilized to estimate the model parameters by means of the maximum likelihood estimation method. Second, the subway incident data from 2012 will be further employed to test the temporal transferability of the developed subway incident delay model. This study will examine the effects of the influencing factors on subway incident delays and provide possible suggestions for the mitigation of subway incident delays.

The main contribution of this study is that it makes an initial attempt to develop a subway operation incident delay estimation model that can be used to predict subway operation incident delays accurately. In addition, the relationship between subway incident delays and influencing factors has been comprehensively examined in this study. The results are useful for public transportation authorities to implement effective strategies to mitigate the negative consequences caused by subway operation incidents.

4. Data

4.1. Data collection

Subway operation incident data were collected from the database published by the Legislative Council of Hong Kong. We also used Google Search as the second channel to obtain subway operation incidents data from various incident reports published online. Two different data samples were used for model development and temporal transferability testing. The first data sample included 1006 incident records from 2005 to 2011; this sample was used to develop the subway operation incident delay model. The second dataset is comprised 122 subway operation incident records from 2012; this dataset was applied to test the temporal transferability of the developed model. Therefore, a total of 1128 subway operation incidents were collected for analysis in this study. Note that each subway operation incident record contains the following information: (i) time; (ii) subway line; (iii) the causes of the incident; and (iv) the incident consequence (i.e., incident delay in minutes).

4.2. Variable descriptions

Singapore Mass Rapid Transit (known as SMRT) recorded subway incidents where the incident delay was longer than 5 min.

Table 1
Variable description.

Variable	Description	Value	Incident delay	
			Mean (minute)	Std error (minute)
Power failure	No	0	14.00	11.90
	Power cable failure	1	38.73	52.58
	Power equipment failure	2	22.86	49.24
Vehicle failure	No	0	15.27	20.76
	Vehicle failure	1	13.91	16.01
Signal failure	No	0	15.58	21.39
	Signal cable failure	1	14.58	5.50
	Signal equipment failure	2	13.73	7.39
Crash	No	0	14.64	19.75
	Crash with casualty	1	19.02	17.95
	Crash without casualty	2	17.55	20.96
Railway turnout malfunction	No	0	15.48	21.11
	Turnout communication disruption	1	14.81	6.76
	Turnout mechanical abrasion	2	13.14	5.84
Operation error	No	0	15.62	20.86
	Operation-internal	1	12.08	7.74
	Operation-external	2	19.21	24.35

Unlike SMRT, incidents that produce no less than 8 min of delay were recorded by Hong Kong Mass Transit Railway (MTR). Only those incidents that caused at least 8 min of delay for the passengers were analyzed in this study because MTR only reported incidents resulting in delays longer than 8 min. Because travel delays resulting from a subway operating incident are the major consequence concerning passengers, incident delays are considered as the target variable in this study.

According to previous studies (i.e., Chow et al., 2004), there are six main factors affecting subway operation incident delays, including power failure, subway vehicle failure, signal failure, crash, railway turnout failure and operation error. Detailed descriptions of these factors are given below.

(i) Power failure. Power failure might be due to power cable disconnection or breakage. Power equipment falls can also cause power failure. Once a power failure occurs, trains may lose traction dynamics or lose communication with the stations and other trains.
(ii) Subway vehicle failure. Vehicle failure mainly includes traction failure, brake system failure, or mechanical malfunction. Traction failure is usually induced by power failure and bow pantograph failure. Brake system failure is related to mechanical components and driver operations. Mechanical malfunction indicates that the several vehicle components break down or that on-board units work abnormally.
(iii) Signal failure. Signal failure could occur in various subway system components, such as rail equipment, cables, station equipment, vehicles, signal computers, etc. In this study, signal failure is regarded as a binary variable.
(iv) Crash. Two types of crashes are considered in this study: (1) crash causing fatalities or injuries and (2) crash not involving casualties, e.g., a crash between the subway train vehicle and fixed objects.
(v) Railway turnout malfunction. Railway turnout malfunction indicates a malfunction of the subway rail turnout (joint between lines used for guiding the subway train). There are two types of railway turnout malfunction, including railway turnout communication disruption and mechanical abrasion.
(vi) Operation error. Operation errors may be caused by internal and/or external factors. Driver mishandling or abnormal passenger behavior are internal factors. Weather or climate factors are external factors.

All of the explanatory variables mentioned above are assigned binary or nominal values. More details on variable information are provided in Table 1.

4.3. Descriptive statistical analysis

Table 1 shows the average subway operation incident delay with respect to different variable values. As expected, power failures and crashes caused a longer average operation incident delay compared with no power failures or no crashes. Table 2 gives the statistics of the selected variables for the years 2005–2012. Approximately 88% of subway operation incidents did not involve power failure in 2005. Similar statistics were found for the other years. The distribution of the subway turnout malfunction was also similar for different years, as was the data related to the operation errors.

However, other variables (e.g., vehicle failure, signal failure, crash) varied substantially in different years. For example, the proportions of subway incidents involving the failure of signal equipment (i.e., signal failure = 2) generally decreased from 0.354 to 0.066 between 2005 and 2012. The reduction of the number of signal failures might be due to the effective management strategies adopted by MTR since 2006. Likewise, fewer and fewer subway incidents are found to be involved in subway vehicle failure after the use of advanced vehicle manufacturing technologies.

Fig. 1 presents a histogram of subway operation incident delays. The figure shows that the incident delay distribution is positively skewed and that the frequency generally decreases as the incident delay increases. In other words, there is a lower occurrence frequency of major subway operation incidents that cause long incident delays compared with minor subway incidents causing short incident delays. It can also be found that the standard deviation of the subway incident delay (=20.36 min) is substantially larger than the mean (=15.31 min). In addition, we can clearly see that the distribution for the incident delay has a long tail. These findings are consistent with the study conducted by Wang et al. (2012).

5. Model development

As mentioned, there is a large variance in subway incident delays, suggesting that it is more appropriate to use probabilistic methods to describe these subway operation incidents. Actually, the hazard-based modeling technique has been extensively used in the transportation field, such as for clearance time analysis (e.g.,

Table 2
Distribution of subway operation incidents in different years.

Variable	Value	2005	2006	2007	2008	2009	2011	2012
Power failure	0	0.879	0.887	0.866	0.898	0.913	0.881	0.910
	1	0.051	0.048	0.027	0.021	0.006	0.036	0.016
	2	0.071	0.065	0.107	0.080	0.081	0.083	0.074
Vehicle failure	0	0.737	0.679	0.631	0.743	0.773	0.810	0.836
	1	0.263	0.321	0.369	0.257	0.227	0.190	0.164
Signal failure	0	0.606	0.756	0.856	0.813	0.837	0.929	0.918
	1	0.040	0.006	0.000	0.016	0.023	0.000	0.016
	2	0.354	0.238	0.144	0.171	0.140	0.071	0.066
Crash	0	0.828	0.720	0.668	0.594	0.616	0.893	0.754
	1	0.081	0.071	0.075	0.102	0.105	0.036	0.098
	2	0.091	0.208	0.257	0.305	0.279	0.071	0.148
Railway turnout malfunction	0	0.838	0.869	0.877	0.791	0.808	0.810	0.852
	1	0.081	0.071	0.075	0.102	0.105	0.131	0.098
	2	0.081	0.060	0.048	0.107	0.087	0.060	0.049
Operation errors	0	0.889	0.863	0.909	0.840	0.791	0.857	0.811
	1	0.081	0.077	0.053	0.090	0.110	0.119	0.156
	2	0.030	0.060	0.037	0.070	0.099	0.024	0.033

Jones et al., 1991; Gilbert, 1992; Wang et al., 2012), traffic incident analysis (Nam and Mannering, 2000; Chung, 2010), etc. Because the hazard-based concepts in probabilistic methods are well-suited for the analysis of time-related data (Hensher and Mannering, 1994), we also employ this method to describe the subway operation incident delay in this study.

5.1. Accelerated failure time (AFT) models

AFT models are effective parametric approaches that can incorporate the effect of external covariates on hazard function (Greene, 2002). In addition, AFT models are able to capture the direct effect of exposure on survival time (Kleinbaum, 1998). Considering these model attributes, the AFT model is applied to estimate subway operation incident delays in this study.

In the AFT model, a subway operation incident delay is considered a continuous variable T with a probability density function $f(t)$ and a cumulative distribution function $F(t)$. Here, $F(t)$ is also known as the failure function and gives the probability of a subway incident resulting in a delay less than a specific time t. In contrast, the survival function, denoted by $S(t)$, is the probability of the incident delay being greater than t. The relationship between $F(t)$ and $S(t)$ is expressed by

$$F(t) = Pr(T \le t) = 1 - Pr(T > t) = 1 - S(t) \quad (1)$$

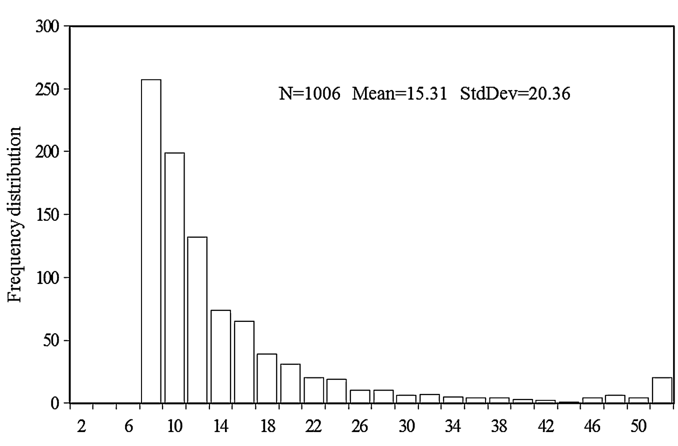

Fig. 1. Frequency distribution of subway operation incident delay.

The hazard function, denoted by $h(t)$, is the ratio of the probability density function to the survival function, given by:

$$h(t) = \frac{f(t)}{S(t)} \quad (2)$$

In the AFT model, one assumption is that there exists a linear relationship between the log of incident delay T and a vector of explanatory variables $\boldsymbol{X}$.

$$\ln(T) = X\beta + \varepsilon \quad (3)$$

where ε is a random error-term and β is a vector of the coefficients to be estimated. More detailed statistical descriptions of hazard-based models can be found in Washington et al. (2011).

5.2. AFT model for three different distributions

With fully parametric models, a variety of distributional alternatives for the hazard function are available for an incident delay, including exponential, Weibull, log-logistic and lognormal distributions. In contrast, only the exponential and Weibull distributions can accommodate proportional hazard (PH) assumptions (Jenkins, 2005). In this study, the full parametric model was also developed to determine the functional form for Eq. (3). Three distributional alternatives were taken into account, namely lognormal, log-logistic and Weibull. The best-fitted distribution models can be determined using the maximum likelihood estimation (MLE) method.

Because the delay in each reported incident case is over 8 min, the distribution should be truncated. For instance, the difference between the log-logistic distribution and the truncated log-logistic distribution is given as:

$$f_{\log-\text{logistic}} = \frac{\beta/\alpha\left(x/\alpha\right)^{\beta-1}}{\left[1+\left(x/\alpha\right)^{\beta}\right]^{2}} \quad (4)$$

$$f_{\text{truncated log}-\text{logistic}} = \frac{f_{\log-\text{logistic}}}{1-\int_0^C f_{\log-\text{logistic}}} \quad (5)$$

where $f_{\log-\text{logistic}}$ denotes the probability density function for the log-logistic distribution; $f_{\text{truncated log-logistic}}$ represents the probability density function of the truncated log-logistic distribution; α and β are the scale parameter and shape parameter of the distribution, respectively; and C is the left boundary of the incident delay, which is equal to 8 min in this study.

Table 3
The estimated coefficients.

Variable	Fixed parameters								Random parameters					
	Lognormal		Log-logistic		Weibull		Weibull with gamma heterogeneity		Lognormal		Log-logistic		Weibull	
	Parameter	t	Parameter	t	Parameter	t	Parameter	t	Parameter	t	Parameter	t	Parameter	t
Intercept	2.3^{***}	37.2	2.28^{***}	37.3	2.48^{***}	27.4	–	–	2.35^{***}	46.5	2.30^{***}	45.6	2.56	50.7
Std. Dev.[a]	–	–	–	–	–	–	–	–	0.63^{***}	5.55	–	–	–	–
Power cable failure	0.63^{***}	5.81	0.33^{*}	41.9	1.34^{***}	8.6	2.10^{***}	22.6	0.59^{**}	2.81	0.65^{**}	3.22	0.55	2.65
Std. Dev	–	–	–	–	–	–	–	–	0.97^{**}	3.22	0.87^{**}	2.98	0.9^{**}	3.13
Power equipment fault	0.37^{***}	4.6	0.23^{**}	2.75	1.00^{***}	8.3	2.24^{***}	32.0	0.32^{***}	3.34	0.33^{***}	3.9	0.28	2.78
Std. Dev	–	–	–	–	–	–	–	–	0.42^{***}	4.82	0.17^{**}	2.83	0.4^{***}	5.17
Vehicle failure	0.12^{*}	1.88	0.06	3.11	0.26^{**}	2.7	2.15^{***}	44.7	0.08	1.35	0.04	0.82	0.01	0.23
Std. Dev	–	–	–	–	–	–	–	–	0.14^{***}	5.15	–	–	0.18^{***}	8.91
Signal cable failure	0.3^{*}	1.95	0.32^{**}	1.14	0.13	0.6	1.73^{***}	16.4	0.22^{*}	2.18	0.30^{*}	2.55	0.15	1.32
Std. Dev	–	–	–	–	–	–	–	–	0	0	–	–	–	–
Signal equipment fault	0.21^{**}	3.04	0.19^{**}	2.44	0.18	1.8	2.28^{***}	44.8	0.17^{**}	2.95	0.17^{**}	3.01	0.10	1.67
Std. Dev	–	–	–	–	–	–	–	–	0.09^{**}	3.24	–	–	0.11^{***}	5.73
Crash with casualty	0.41^{***}	5.21	0.33^{***}	3.05	0.60^{***}	5.3	2.38^{***}	42.4	0.36^{***}	4.44	0.38^{***}	4.99	0.32	3.8
Std. Dev	–	–	–	–	–	–	–	–	0.31^{***}	5.29	0.16^{***}	3.64	0.28^{***}	5.83
Crash without casualty	0.25^{**}	3.12	0.20^{**}	4.46	0.25^{*}	2.2	2.24^{***}	30.5	0.17^{**}	2.28	0.16^{*}	2.46	0.12	1.48
Std. Dev	–	–	–	–	–	–	–	–	0.09^{*}	2.32	–	–	0.15^{***}	4.18
Turnout communication disruption	0.32^{***}	3.8	0.32^{***}	2.71	0.25^{*}	2.1	2.45^{***}	35.9	0.26^{***}	3.95	0.30^{**}	4.41	0.19	2.66
Std. Dev	–	–	–	–	–	–	–	–	0.06	1.95	–	–	0.07^{**}	3.13
Turnout abrasion	0.2^{*}	2.39	0.19^{**}	4.31	0.13	1.1	2.31^{***}	31.7	0.15^{*}	2.24	0.17^{*}	2.46	0.19	3.1
Std. Dev	–	–	–	–	–	–	–	–	0.05	1.65	–	–	–	–
Operation-internal	0.08	1.19	0.06	2.54	0.04	0.4	2.21^{***}	38.0	0.03	0.45	0.03	0.59	−0.06	−0.89
Std. Dev	–	–	–	–	–	–	–	–	0.05^{*}	1.98	0.03^{**}	3.85	0.1^{***}	5.88
Operation-external	0.18^{**}	2.33	0.11	0.89	0.20	1.9	0.38^{***}	5.8	0.10	1.33	0.07	1.03	0.17	2.45
Std. Dev	–	–	–	–	–	–	–	–	0.11^{*}	2.02	0.09^{*}	2.11	–	-
Scale	0.5^{***}	45.1	0.25^{***}	37.3	0.7^{***}	50.6	2.10^{***}	22.6	0.29^{***}	9.05	0.22^{***}	33.3	0.30	27.26
θ	–		–		–		0.19^{***}	26.6						
−2LL	6369		6381		7165		7029		6361		6307		6568	
Sample size	1006		1006		1006		1006		1006		1006		1006	
No. of covariates	11		11		11		12		11		11		11	
AIC	6393		6405		7189		7053		6409		6341		6608	

[a] Standard deviation of normally distributed parameter.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Hence, the hazard function in an AFT model with a truncated log-logistic distribution can be defined by

$$h(t)_{\text{log-logistic}} = \frac{\lambda p(\lambda t)^{p-1}}{1+(\lambda t)^{p}} \quad (6)$$

$$h(t)_{\text{truncated log-logistic}} = \frac{f_{\text{truncated log-logistic}}}{1-\int_0^t f_{\text{truncated log-logistic}}} \quad (7)$$

where λ and p are the location parameter and scale parameter of the AFT model, respectively.

It should be noted that the above AFT models with fixed parameters assume that the effect of an individual variable is the same for each observed case. In other words, they assume that the incident delay is homogeneous across different observations, which might be inconsistent with reality. Obviously, an improperly specified model may lead to erroneous inference results. In this study, one efficient approach adopted to examine the homogeneity associated with incident delays is the use of the gamma distribution over the population with a mean of 0 and a variance of θ in an attempt to incorporate the heterogeneity into the Weibull model. The hazard function of a Weibull model with gamma heterogeneity distribution can be expressed by

$$h(t) = \frac{\lambda p(\lambda t)^{p-1}}{1+\theta(\lambda t)^{p}} \quad (8)$$

Another alternative adopted to incorporate the unobserved heterogeneity is to introduce random parameters for the AFT model (Washington et al., 2011; Anastasopoulos et al., 2012; Anastasopoulos and Mannering, 2014). The difference between the fixed and random parameters for the AFT model is that the latter is added by a randomly distributed term ω_n. Namely, a random parameter can be expressed by

$$\beta_n = \beta + \omega_n \quad (9)$$

where β_n is the random parameter term varying with different observations; β is the fixed parameter; and the random error term ω_n follows $N(0, \sigma^2)$. In general, this method allows for the correlation across random parameters, the examination of which may

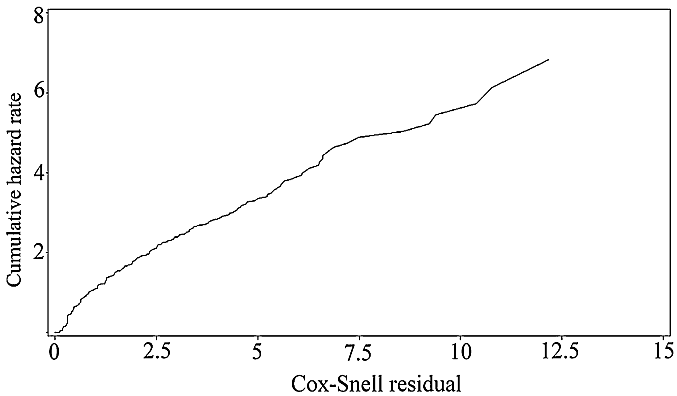

Fig. 2. Graph of the cumulative hazard of the Cox-Snell residual under the log-logistic AFT model.

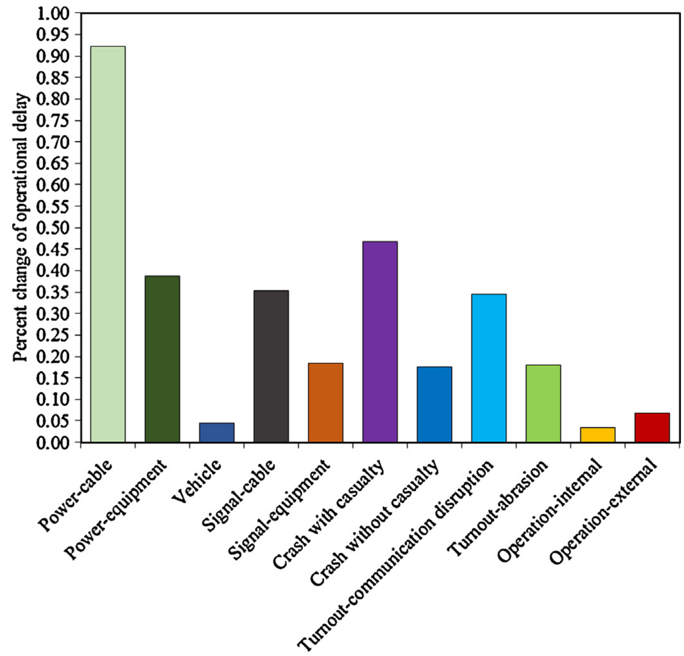

Fig. 3. Relative changes in subway operation incident delays.

yield insights into the data generating process for the underlying heterogeneity (Hojati et al., 2013). It should be noted that not all the parameters should be considered as random parameters. In this study, we use a method to determine which parameter should be regarded as a random parameter for the AFT model. More specifically, this method starts with the AFT model with fixed parameters (no random parameters). For each explanatory variable, we calculate the log-likelihood (i.e., Ln(L)) of the AFT model by means of the simulated maximum likelihood estimation method if the corresponding parameter is regarded as a random parameter. The random parameter that could yield the smallest value for the Akaike information criterion (AIC = $2N - 2\text{Ln}(L)$, where N is the number of parameters) will be used by the model. One more random parameter is considered, and then we calculate the log-likelihood again. Hence, the random parameters are added one by one to the model until no random parameters could improve the model's performance.

6. Results and discussions

The fixed parameters for the AFT model can be estimated by a maximum likelihood estimation. The random parameter is determined by means of the simulated maximum likelihood estimation method using Halton draws (Washington et al., 2011). The variables defined above, namely, power failure, vehicle failure, signal failure, crash, railway turnout malfunction and operation error, were used to determine the AFT model.

Table 3 gives the parameter estimates for the seven AFT models for the subway operation incident delay. The table shows that the log-logistic AFT model with random parameters could provide the best fit for the incident delay because of the smallest AIC value (6341) compared with those from the other AFT models. An overall goodness-of-fit for the AFT model can be assessed using the Cox-Snell residuals, which are frequently used as a means to check whether the data support a particular parametric form of the hazard function. Fig. 2 presents the Cox-Snell residual for the log-logistic AFT model. According to the figure, it can be observed that the plotted points fall closer to a straight line, suggesting that the predicted incident delay from the log-logistic AFT model matches the observed data well. Therefore, similar to previous studies (Nam and Mannering, 2000; Stathopoulos and Karlaftis, 2002), we selected the log-logistic AFT model with random parameters for the final analysis in this study.

To gain further insight into the effects of the influencing factors on the subway operation incident delay, we can use the exponents of the estimated coefficients to interpret the results. The exponents of the coefficients, with all coefficients typically evaluated at their mean values, translate to a percent change in subway incident delays resulting from one unit increase for continuous explanatory variables and a change from 0 to 1 for indicator variables (Garavaglia and Sharma, 2004). For example, the exponential coefficient of power cable failure is 1.922 ($\approx$exp(0.65)), indicating that the incident delay is 92.2% longer for subway incidents caused by power cable failure than incidents not involving power cable failure.

Fig. 3 depicts the effects of these factors on incident delays. According to the percentage changes in Fig. 3, most of the results are consistent with the univariate analysis results in Table 1. The figure shows that delays caused by subway incidents involving a power equipment fault are 38.7% longer on average compared incident delays not attributed to power equipment failure. Longer incident delays caused by power failure (including power cable failure and power equipment fault) might be explained by the fact that it is difficult for engineers to detect and locate the problem. In addition, power failure could lead to the secondary failure of other subway operation facilities, such as signal computers. Comparing power cable failure and power equipment fault, cable failure causes longer incident delays than equipment fault on average. This finding is consistent with the reality that engineers usually replace rather than repair failing equipment, especially in an emergency situation (Zimmerman, 2004). Hence, it will take less time to replace failing equipment than to detect power cable failure. One suggestion is that subway engineers and decision-makers should employ backup power equipment, such as standby power generator, to shorten the time for replacing failing power equipment. In addition, a number of subway fire accidents that lead to long delays are primarily caused by power cable disconnection (He et al., 2005). Therefore, flame-resistant materials are recommended for isolating electrical equipment and public areas. Adequate battery-powered lighting and good ventilation should be provided to mitigate the consequences of fire accidents.

Fig. 3 shows that vehicle failure has the least impact on the increment of subway operation incident delays. Vehicle failure only increased incident delays by 4.4%. One possible reason for the minor impact is that no additional facility and rescue teams are involved in the recovery process for subway incidents caused by vehicle failure. Therefore, the average incident delay is not greatly increased. However, crashes involving casualties cause larger increase in incident delays (approximately 46.8% longer than non-crash incidents) because the staff will undertake major efforts to rescue the victims rather than restart the train. Second, onlookers in the confined area could be another obstacle for fast response. Third, accident liability has to be justified before the subway system returns to normal. Compared with crash incidents that involve casualties, crash incidents not involving casualties caused much shorter delays. This result is reasonable because there is no need to spare more time to rescue injured people first. The foremost task of the staff is to keep the rail track clear and the system running as efficiently as possible.

Fig. 3 also shows that signal cable failure and signal equipment fault increased incident delays by 35.4% and 18.5%, respectively. This result suggests that advanced communication technologies (e.g., short-distance and wireless communication technology such as Wifi and Zigbee) should be introduced into the subway system to decrease the probability of signal cable failure. We found that turnout communication disruption led to an approximately 16.5% (=34.5–18%) longer incident delay than turnout abrasion. The longer incident delay associated with turnout communication disruption might be because the corresponding response procedures are more complicated than those for turnout abrasion. Once there is a turnout communication disruption, the rail track turnout may not respond to the signal control without warning. Under this condition, the subway train may deviate from the normal route thus producing operation delays. A feedback mechanism should be established to detect the turnout communication disruption and respond immediately once such an incident occurs. When there is turnout abrasion, the rail track turnout cannot be set automatically. Nevertheless, working staff can go down onto the rail tracks and set the turnout manually. Hence, turnout abrasion produces a shorter delay compared with communication disruption. To reduce the occurrence likelihood of turnout abrasion, daily maintenance and special care of the turnout should be emphasized.

7. Temporal transferability

The subway incident delay estimation model was developed using a data sample from 2005 to 2011. It is necessary to test whether the estimates of the coefficients are valid over time. Temporal transferability ensures that estimations made with the model have some validity in that the estimated parameters are stable over time (Washington et al., 2011). A second data sample, from 2012, was utilized to justify the validity. A likelihood ratio test was conducted to validate the temporal transferability. The likelihood ratio test is a statistical test used to compare the fit of two models, one of which (the null model) is a special case of the other (the alternative model). The test is based on the likelihood ratio, which reflects how many times more likely the data are under one model than the other (Neyman and Pearson, 1992).

According to Washington et al. (2011), the test statistic (often denoted by D) can be defined by

$$
\begin{aligned}
D &= -2\log\left(\frac{\text{likelihood for null model}}{\text{likelihood for alternative model}}\right)\\
&= -2\log(\text{likelihood for null model})\\
&\quad + 2\log(\text{likelihood for alternative model}) \qquad (10)
\end{aligned}
$$

where D follows the chi-square distribution, where the freedom equals the number of covariates. In this study, the likelihood ratio test statistic is given by

$$D = -2[\mathrm{LL}(\beta_\mathrm{T}) - \mathrm{LL}(\beta_\mathrm{a}) - \mathrm{LL}(\beta_\mathrm{b})] \qquad (11)$$

where $\mathrm{LL}(\beta_\mathrm{T})$ is the log-likelihood at the convergence of the model using the total data (both the 2005–2011 data and the 2012 data), and $\mathrm{LL}(\beta_\mathrm{a})$ is the log-likelihood at the convergence of the model using 2005–2011 data. $\mathrm{LL}(\beta_\mathrm{b})$ refers to the log-likelihood of the model using the 2012 data. D equals 20.3, and the corresponding p-value is 0.249. There are several possible explanations for the fact that the p-value is a little small. One explanation is that the framework of Hong Kong subway operation and management has been changed. Two independent subway systems merged to create MTR in December of 2007, and the incident reporting scheme was unified accordingly. The scale and accident distribution pattern have been slightly changed. In addition, the small p-value might most likely be the result of the limited data. Nevertheless, the results still show that the estimated coefficients in the developed subway operation incident delay model are stable over time to a large extent.

8. Conclusions and recommendations

This study has developed a subway operation incident delay model using archived Hong Kong subway incident data. Both fixed and random effects were considered for the parametric accelerated failure time (AFT) models including log-logistic, lognormal and Weibull models. Additionally, the Weibull model with gamma heterogeneity was also generated to examine the heterogeneity. Based on six-year subway incident datasets from 2005 to 2011, the model parameters were calibrated using the maximum likelihood estimation method and were further used to predict the delay caused by subway operation incidents. In addition, the subway incident data in 2012 were utilized to test the temporal transferability of the developed models.

The results show that the log-logistic AFT model with random parameters could provide the best fit for the incident delay, and it was thus selected for the final analysis in this study. The results clearly indicate that longer subway operation incident delays are significantly influenced by power cable failure, signal cable failure and turnout communication disruption. Vehicle failure has the least impact on the increment of subway operation incident delay. According to these results, we can suggest that decision makers should employ backup power equipment such as a standby power generator to shorten the time required for replacing failing power equipment. Short-distance and wireless communication technology (e.g., Wifi and Zigbee) should be introduced into the subway system to reduce the probability of signal cable failure. Daily maintenance on rail track turnout should be emphasized. Consistent with our expectation, it was also found that crash incidents not involving casualties could cause much shorter incident delay than crash incidents involving casualties.

The temporal transferability test results show that the estimated parameters for the log-logistic distributed AFT model with random parameters appear to be stable over time. Therefore, the developed subway incident model can be utilized to make subway incident delay predictions as soon as the basic incident information is reported. In addition, the impact analysis of the factors that influence incident delays could help decision makers formulate rational and timely diversion and dispatching decisions to mitigate the negative consequences (i.e., delay) resulting from subway incidents. The results are of considerable utility for evaluating the potential impact of different incident management strategies.

Further research will be conducted to collect more subway incident data, not only from Hong Kong subways but also from other cities. Additional factors, such as the underground flow characteristics and the physical capacity of a station, will also be taken into account in the future.

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