U.S. Department of
Transportation

**Federal Railroad
Administration**

Start Time Variability and Predictability in Railroad Train and Engine Freight and Passenger Service Employees

Office of Research
and Development
Washington, DC 20590

DOT/FRA/ORD-14/05

Final Report
April 2014

REPORT DOCUMENTATION PAGE	*Form Approved OMB No. 0704-0188*

1. AGENCY USE ONLY (Leave blank)	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	April 2014	Technical Report

4. TITLE AND SUBTITLE

Start Time Variability and Predictability in Railroad Train and Engine Freight and Passenger Service Employees

5. FUNDING NUMBERS

6. AUTHOR(S)

Thomas G. Raslear

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

Federal Railroad Administration
1200 New Jersey Avenue, SE
Washington, DC 20590

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

U.S. Department of Transportation
Federal Railroad Administration
Office of Railroad Policy and Development
Office of Research and Development
Washington, DC 20590

10. SPONSORING/MONITORING AGENCY REPORT NUMBER

DOT/FRA/ORD-14/05

11. SUPPLEMENTARY NOTES

COR: Thomas G. Raslear

12a. DISTRIBUTION/AVAILABILITY STATEMENT

This document is available to the public through the FRA Web site at http://www.fra.dot.gov.

12b. DISTRIBUTION CODE

13. ABSTRACT (Maximum 200 words)

Start time variability in work schedules is often hypothesized to be a cause of railroad employee fatigue because unpredictable work start times prevent employees from planning sleep and personal activities. This report examines work start time differences from three different databases previously published by the Federal Railroad Administration: the Fatigue Accident Validation database, the Work Schedules and Sleep Patterns of Train and Engine Service Workers database, and the Work Schedules and Sleep Patterns of Passenger Train and Engine Service Workers database. A statistical description is provided for start time differences for Freight Train and Engine (T&E) crews on days with accidents (Accidents), Freight T&E on days preceding accidents (Pre-accident), T&E on days without accidents (T&E), and Passenger T&E on days without accidents (Passenger T&E). Start time difference unpredictability (σ^2) was ordered as follows: $\sigma^2_{\text{Accidents}} \geq \sigma^2_{\text{Pre-accident}} > \sigma^2_{\text{T\&E}} > \sigma^2_{\text{Passenger T\&E}}$. Fatigue, as measured by the Fatigue Avoidance Scheduling Tool, was significantly correlated with start time difference unpredictability. The start time difference variance and hazard function are useful statistical measures for determining start time variability and predicting fatigue in work schedules.

14. SUBJECT TERMS	15. NUMBER OF PAGES
Work schedules, start time variability, fatigue, train and engine service, accident probability, FAST	27
	16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. 239-18
298-102

METRIC/ENGLISH CONVERSION FACTORS

ENGLISH TO METRIC

LENGTH (APPROXIMATE)

1 inch (in)	=	2.5 centimeters (cm)
1 foot (ft)	=	30 centimeters (cm)
1 yard (yd)	=	0.9 meter (m)
1 mile (mi)	=	1.6 kilometers (km)

AREA (APPROXIMATE)

1 square inch (sq in, in^2)	=	6.5 square centimeters (cm^2)
1 square foot (sq ft, ft^2)	=	0.09 square meter (m^2)
1 square yard (sq yd, yd^2)	=	0.8 square meter (m^2)
1 square mile (sq mi, mi^2)	=	2.6 square kilometers (km^2)
1 acre = 0.4 hectare (he)	=	4,000 square meters (m^2)

MASS - WEIGHT (APPROXIMATE)

1 ounce (oz)	=	28 grams (gm)
1 pound (lb)	=	0.45 kilogram (kg)
1 short ton = 2,000 pounds (lb)	=	0.9 tonne (t)

VOLUME (APPROXIMATE)

1 teaspoon (tsp)	=	5 milliliters (ml)
1 tablespoon (tbsp)	=	15 milliliters (ml)
1 fluid ounce (fl oz)	=	30 milliliters (ml)
1 cup (c)	=	0.24 liter (l)
1 pint (pt)	=	0.47 liter (l)
1 quart (qt)	=	0.96 liter (l)
1 gallon (gal)	=	3.8 liters (l)
1 cubic foot (cu ft, ft^3)	=	0.03 cubic meter (m^3)
1 cubic yard (cu yd, yd^3)	=	0.76 cubic meter (m^3)

TEMPERATURE (EXACT)

[(x-32)(5/9)] °F = y °C

METRIC TO ENGLISH

LENGTH (APPROXIMATE)

1 millimeter (mm)	=	0.04 inch (in)
1 centimeter (cm)	=	0.4 inch (in)
1 meter (m)	=	3.3 feet (ft)
1 meter (m)	=	1.1 yards (yd)
1 kilometer (km)	=	0.6 mile (mi)

AREA (APPROXIMATE)

1 square centimeter (cm^2)	=	0.16 square inch (sq in, in^2)
1 square meter (m^2)	=	1.2 square yards (sq yd, yd^2)
1 square kilometer (km^2)	=	0.4 square mile (sq mi, mi^2)
10,000 square meters (m^2)	=	1 hectare (ha) = 2.5 acres

MASS - WEIGHT (APPROXIMATE)

1 gram (gm)	=	0.036 ounce (oz)
1 kilogram (kg)	=	2.2 pounds (lb)
1 tonne (t)	=	1,000 kilograms (kg)
	=	1.1 short tons

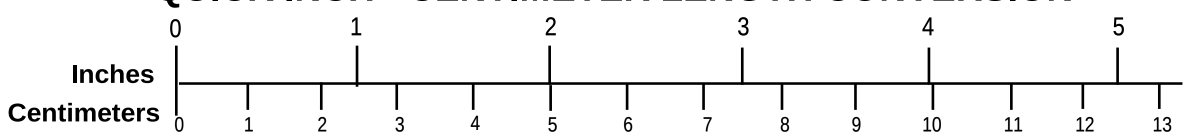
VOLUME (APPROXIMATE)

1 milliliter (ml)	=	0.03 fluid ounce (fl oz)
1 liter (l)	=	2.1 pints (pt)
1 liter (l)	=	1.06 quarts (qt)
1 liter (l)	=	0.26 gallon (gal)
1 cubic meter (m^3)	=	36 cubic feet (cu ft, ft^3)
1 cubic meter (m^3)	=	1.3 cubic yards (cu yd, yd^3)

TEMPERATURE (EXACT)

[(9/5) y + 32] °C = x °F

QUICK INCH - CENTIMETER LENGTH CONVERSION



QUICK FAHRENHEIT - CELSIUS TEMPERATURE CONVERSION

°F	-40°	-22°	-4°	14°	32°	50°	68°	86°	104°	122°	140°	158°	176°	194°	212°
°C	-40°	-30°	-20°	-10°	0°	10°	20°	30°	40°	50°	60°	70°	80°	90°	100°

For more exact and or other conversion factors, see NIST Miscellaneous Publication 286, Units of Weights and Measures. Price $2.50 SD Catalog No. C13 10286

Updated 6/17/98

Acknowledgements

I wish to thank the following individuals who read early versions of this report and provided critical feedback to me: Michael Coplen, Michael Jones, Starr Kidda, and Judy Gertler.

Contents

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Executive Summary

FRA analysis of variability in employee on duty start times from one shift to another shows the order to be:

1. Shifts in which accidents happened—highest
2. Shifts prior to accidents happening
3. Freight Train and Engine shifts
4. Passenger Train and Engine shifts—lowest

High variability in shift start times is found to contribute to human fatigue, which, from previous studies, is known to increase the probability of accidents. Thus, a potential way of increasing safety is to reduce shift start time variability.

This report uses data from three databases: the Fatigue Accident Validation database, the Work Schedules and Sleep Patterns of Train and Engine Service Workers database, and the Work Schedules and Sleep Patterns of Passenger Train and Engine Service Workers database. The Fatigue Accident Validation database has start times for freight train and engine crews on days on which accidents occurred (Accidents) and for days preceding accidents (Pre-accident). The Work Schedules and Sleep Patterns of Train and Engine Service Workers database has start times for train and engine crews on days without accidents (T&E). The Work Schedules and Sleep Patterns of Passenger Train and Engine Service Workers database has start times for passenger train and engine crews on days without accidents (Passenger T&E).

Distributions were calculated from differences in start times between successive shifts, regardless of intervening non-work days. The variances of the distributions indicate that start time unpredictability is related to accidents. Fatigue, as measured by the Fatigue Avoidance Scheduling Tool (FAST), was significantly correlated with start time difference unpredictability. Fatigue is known to increase the probability of certain types of accidents and is the critical intervening variable that mediates the relationship between start time variability and accidents.

The start time difference variance is a useful statistical measure for determining start time variability and predicting fatigue in work schedules without the use of a fatigue model when schedules do not involve a majority of night work. This statistical tool can be used to make model-free comparisons between work locations, types of jobs, and changes in policies and procedures, etc., with regard to fatigue.

1. Introduction

FRA has been conducting research on worker fatigue in the U.S. railroad industry for more than 20 years. Two critical areas were identified early as essential to understanding and managing fatigue (Pilcher and Coplen, 2000). First, data on work and rest schedules was needed to determine the duration and timing of sleep for railroad employees. Second, a fatigue model was needed to allow the estimation of fatigue from data on the duration and timing of employee sleep. A model is necessary because of the complex interaction of circadian, homeostatic, and other non-linear physiological processes in the regulation of sleep and fatigue (Hursh, et al., 2004). Both of these needs have now been satisfied. Data on work and rest schedules has been collected for signalmen (Gertler and Viale, 2006a), maintenance of way employees (Gertler and Viale, 2006b), dispatchers, (Gertler and Viale, 2007), train and engine service employees (Gertler and DiFiore, 2009), and train and engine service employees in passenger operations (Gertler and DiFiore, 2011). A fatigue model has been validated and calibrated for use in the railroad industry (Hursh, Raslear, Kaye and Fanzone, 2008). The data and fatigue model have been used to successfully characterize work and sleep patterns and to accurately estimate fatigue for railroad employees (Gertler, DiFiore and Raslear, 2013, Raslear, Gertler and DiFiore, 2013). Data collected to validate and calibrate the fatigue model has been used to more precisely quantify the relationship between fatigue levels and accident probability (Raslear, Hursh and Van Dongen, 2011). Despite this progress, there has, to date, been no research documenting the contribution of work schedule predictability to fatigue, even though this issue was highlighted by Pilcher and Coplen in 2000.

Discussions about employee fatigue in the U.S. railroad industry often focus on the predictability of work start times for employees engaged in train and engine (T&E) freight and passenger service. Labor union representatives often argue that unpredictable work start times heavily prevent employees from planning sleep and personal activities, which then results in fatigue. The types of work performed by T&E employees and typical schedules are described in detail in Gertler, DiFiore and Raslear (2013) and Pilcher and Coplen (2000). In summary, T&E employees who work in yards, local freight service, and passenger and commuter operations have jobs with regular start times and high work start time predictability. However, employees on the extra board, which sometimes offers employees additional compensation for volunteering to work additional hours within the statutory limit, have work schedules that may vary from day to day because they fill in for employees with regular assignments. These jobs have lower work start time predictability. Jobs in passenger service often have a split assignment in which the employee works the morning rush, has time off in the middle of the day (referred to as “interim release”), and returns to work for the evening rush. Interim release is usually 4 hours or more. These jobs often have high work start time predictability. T&E employees who work in road freight service often do not have a regular work schedule as far as the days that they work or the time that their work starts. These jobs have low start time predictability. This report describes two measures of start time variability or predictability and relates start time predictability to fatigue and accidents.

1.1 Logic of Approach

In what follows, the notation $y = f(x)$ means that y is a function of x, and the notation $p(y)= f(x)$ means that the probability of y is a function of x.

- Work schedules determine when and how much employees sleep (Gertler et al., 2013; Raslear, Hursh and Van Dongen, 2011):

  $$\textit{sleep schedules} = f(\textit{work schedules}). \tag{1}$$

- Sleep schedules determine employee fatigue levels (Gertler et al., 2013; Raslear et al., 2011):

  $$\textit{fatigue} = f(\textit{sleep schedules}). \tag{2}$$

- Increased fatigue levels have been demonstrated to increase the risk and probability of human factor accidents (Hursh, Raslear, Kaye and Fanzone, 2008; Raslear et al., 2011):

  $$p(\textit{accident}) = f(\textit{fatigue}), \tag{3}$$

  from which it follows that

  $$p(\textit{accident}) = f(\textit{work schedules}). \tag{4}$$

- One aspect of any work schedule is its start time variability. It is hypothesized that

  $$p(\textit{accident}) = f(\textit{start time variability}). \tag{5}$$

- FRA has data on the fatigue level of freight T&E service employees involved in human factor accidents ($fatigue_{Accident}$; Hursh et al., 2008) and on the fatigue level of T&E freight ($fatigue_{T\&E}$) and passenger ($fatigue_{Pass\ T\&E}$) service employees who were not involved in human factor accidents (Gertler et al., 2013). From these reports we know that

  $$fatigue_{Accident} > fatigue_{T\&E} > fatigue_{Pass\ T\&E}. \tag{6}$$

- These fatigue levels were estimated with the Fatigue Avoidance Scheduling Tool (FAST) which requires 3 days of work schedules to produce an accurate estimate. Below, we examine start time variability on days with accidents and days preceding accidents from the same database. Because the same data is used, fatigue estimates for days with accidents and for days preceding accidents are confounded. It is possible that the fatigue on days with accidents is greater than or equal to the fatigue on days preceding accidents. Therefore, we conservatively state that

$$fatigue_{Accident} \geq fatigue_{Preceding\ Accident} > fatigue_{T\&E} > fatigue_{Pass\ T\&E} \quad (7)$$

- It is well known that accident rates are higher in freight service than in passenger service (mean train accident rate for Class I railroads (excluding Amtrak) = 3.25 accidents per million train miles (MTM); for Amtrak and commuter railroads = 2.06 accidents per MTM; $t = 4.63$, $df = 18$, $p < 0.01$; see Fig. 1). This is consistent with the fatigue data for freight and passenger T&E employees as expressed in equation (7) and with the conclusions about fatigue and accidents in equations (3) and (4). Therefore, if the hypothesis in equation (5) is correct, we predict that start time variability will be ordered

$$Accident\ Day \geq Preceding\ Accident > T\&E > Passenger\ T\&E. \quad (8)$$

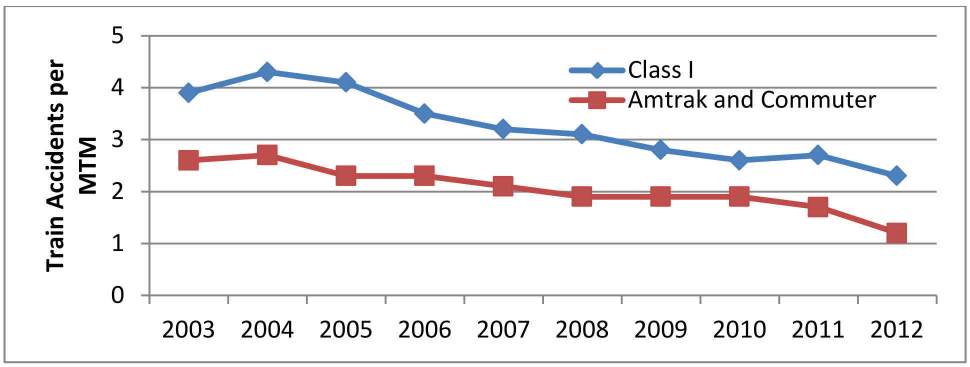

Figure 1. Train accidents per million train miles from the FRA accident database (http://safetydata.fra.dot.gov/OfficeofSafety/Default.aspx).

2. Methods

Start time differences for T&E employees were obtained from three previously published FRA databases. The Fatigue Accident Validation database (FAV, http://www.fra.dot.gov/eLib/details/L03039, FRA, 2011) was used to obtain start times for freight T&E employees on days with human factors (HF) accidents and to obtain start times on days preceding HF accidents. The Work Schedules and Sleep Patterns of Train and Engine Service Workers database (http://www.fra.dot.gov/Page/P0604, FRA 2008) was used to obtain start times for T&E employees who were not involved in an accident during the data collection period.[1] Likewise, the Work Schedules and Sleep Patterns of Passenger Train and Engine Service Workers database (http://www.fra.dot.gov/Page/P0604, FRA 2008) was used to obtain start times for passenger service T&E employees who were not involved in an accident during the data collection period. Details about the data collection processes for these databases can be found in three FRA reports (for FAV see Hursh, Raslear, Kaye and Fanzone, 2008; for the Work Schedules and Sleep Patterns of Train and Engine Service Workers database see Gertler and DiFiore, 2009; for the Work Schedules and Sleep Patterns of Passenger Train and Engine Service Workers database see Gertler and DiFiore, 2011). Table 1 shows the sample sizes from which start time distributions were generated.

Table 1. Start Time Difference Distributions, Sample Sizes, and Databases Used in This Report.

Distribution	Sample Size	Database
Freight T&E, Day of Accidents	704	Fatigue Accident Validation
Freight T&E, Days Preceding Accidents	11,876	Fatigue Accident Validation
T&E (93% Freight), Days without Accidents	2,412	Work Schedules and Sleep Patterns of Train and Engine Service Workers
Passenger T&E, Days without Accidents	3,347	Work Schedules and Sleep Patterns of Passenger Train and Engine Service Workers

Start time difference distributions were generated by calculating the difference in start times between successive shifts, regardless of intervening non-work days. For example, if an employee starts work on Tuesday at 0800 and at 1000 on Thursday (the next work start), the start time difference is +2 hours. If an employee starts on Tuesday at 0800 and the next work start is at 0600, the start time difference is -2 hours. Multiple starts in the same day are treated the same way. Higher level patterns of work (e.g., split shifts in passenger service or yard assignments in freight service) were not examined, which allows for a comparison across the data sets, but may underestimate predictability for some types of service.

[1] A small number of passenger service employees (7% of cases) are included in this database. Ninety-three percent of the cases are employees in freight service.

Each distribution was plotted as an empirical probability density function (pdf), and the mean (μ), variance (σ^2), standard deviation (σ), and hazard function were calculated (Evans, Hastings and Peacock, 2000). The pdf plots were used to visually determine whether the distributions conformed to any of the distributions that have been mathematically described in the statistics and probability literature (Evans et al., 2000; Johnson and Kotz, 1969, 1970a, b). μ provides a measure of the consistency of start times from day to day because it is the expected value of the distribution. σ^2, on the other hand, provides a measure of the inconsistency or unpredictability of start times from day to day relative to μ. σ^2 would be zero only if every start time difference was exactly the same as the mean. σ is the square root of σ^2 and is used to express the variability of a data set in the original measurement units. In a normal distribution, 68 percent of all cases fall within one standard deviation of the mean. Finally, the hazard function was calculated for each distribution. The hazard function is defined as the pdf divided by the survival function. The survival function is 1 minus the cumulative distribution function (cdf), which is the integral of the pdf. The hazard function indicates the likelihood that the next start time will increase, decrease, or remain constant with time since the last start. In engineering, it is known as the failure rate function.

In addition to providing a statistical description of start time differences for Freight T&E on days with accidents (Accidents), Freight T&E on days preceding accidents (Pre-accident), T&E on days without accidents (T&E), and Passenger T&E on days without accidents (Passenger T&E), we hypothesized that start time difference unpredictability (σ^2) would be ordered as follows:

$$\sigma^2_{\mathrm{Accidents}} \geq \sigma^2_{\mathrm{Pre-accident}} > \sigma^2_{\mathrm{T\&}E} > \sigma^2_{\mathrm{Passenger\ T\&}E} \qquad (9)$$

This ordering of the variance of start time differences was based on the logic and evidence outlined in Section 1.1. In equation (9), the variability of start times is formally specified as the variance of the start time distribution.

3. Results

3.1 The Distributions

Figure 2 shows the start time difference distributions for freight T&E on days with accidents (Accidents), Freight T&E on days preceding accidents (Pre-accident), T&E on days without accidents (T&E), and Passenger T&E on days without accidents (Passenger T&E).

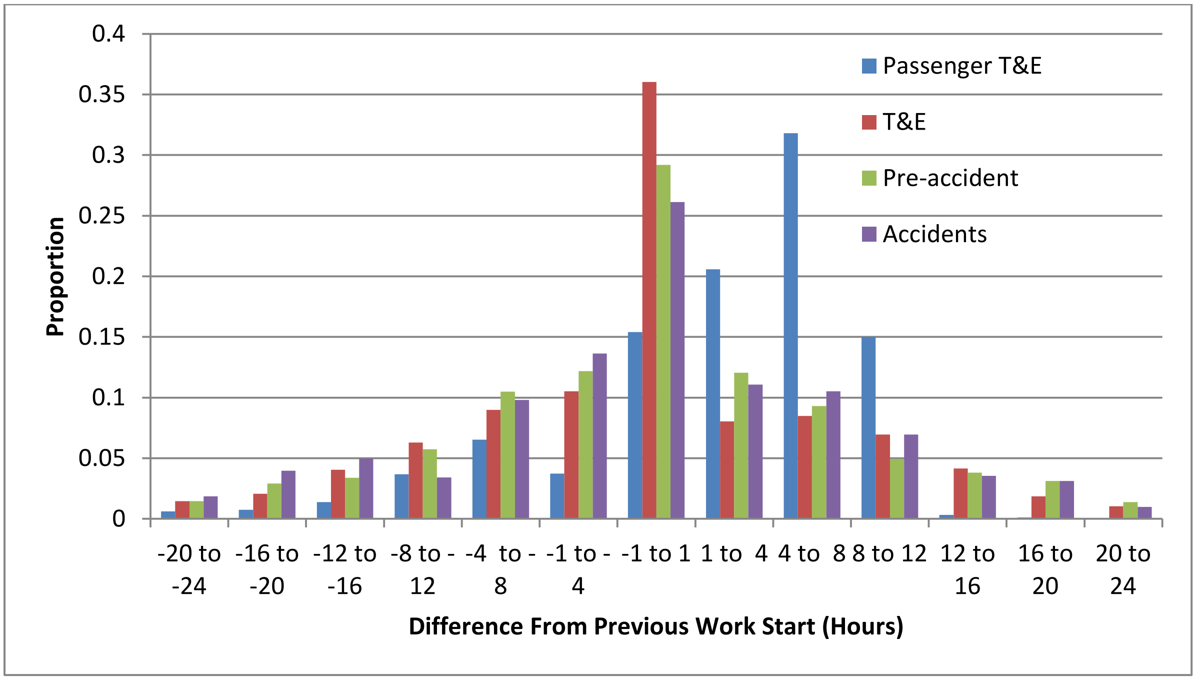

Figure 2. Start time difference distributions. See text for details.

The distributions for Accidents, Pre-accident, and T&E all have a mode at -1 to 1 hours start time difference, but Passenger T&E has a mode at 4 to 8 hours. In addition, the Passenger T&E distribution is not as symmetric as the other distributions. This difference is more obvious in Figures 3 and 4, which show the Passenger T&E distribution separate from the other distributions. The Passenger T&E distribution is highly positively skewed. The Accidents, Pre-accident, and T&E distributions are different from one another in that the Accidents distribution has a lower mode and broader tails than the Pre-accident distribution, which in turn has a lower mode and broader tails than the T&E distribution. χ^2 tests confirm that these three distributions are statistically different (Accidents versus Pre-accident, $\chi^2 = 25.71$, df = 12, $p<0.05$; Accidents versus T&E, $\chi^2 = 50.92$, df = 12, $p<0.05$; T&E versus Pre-accident, $\chi^2 = 107.76$, df = 12, $p<0.05$). The Accidents, Pre-accident, and T&E distributions resemble the Laplace or double-exponential distribution (Evans et al., 2000), but the former are negatively skewed, which is not characteristic of Laplace distributions. It could be the case that each half of these distributions is an exponential distribution. This possibility will be examined in more detail later. The distribution for Passenger T&E does not resemble the other three distributions or any common statistical distribution.

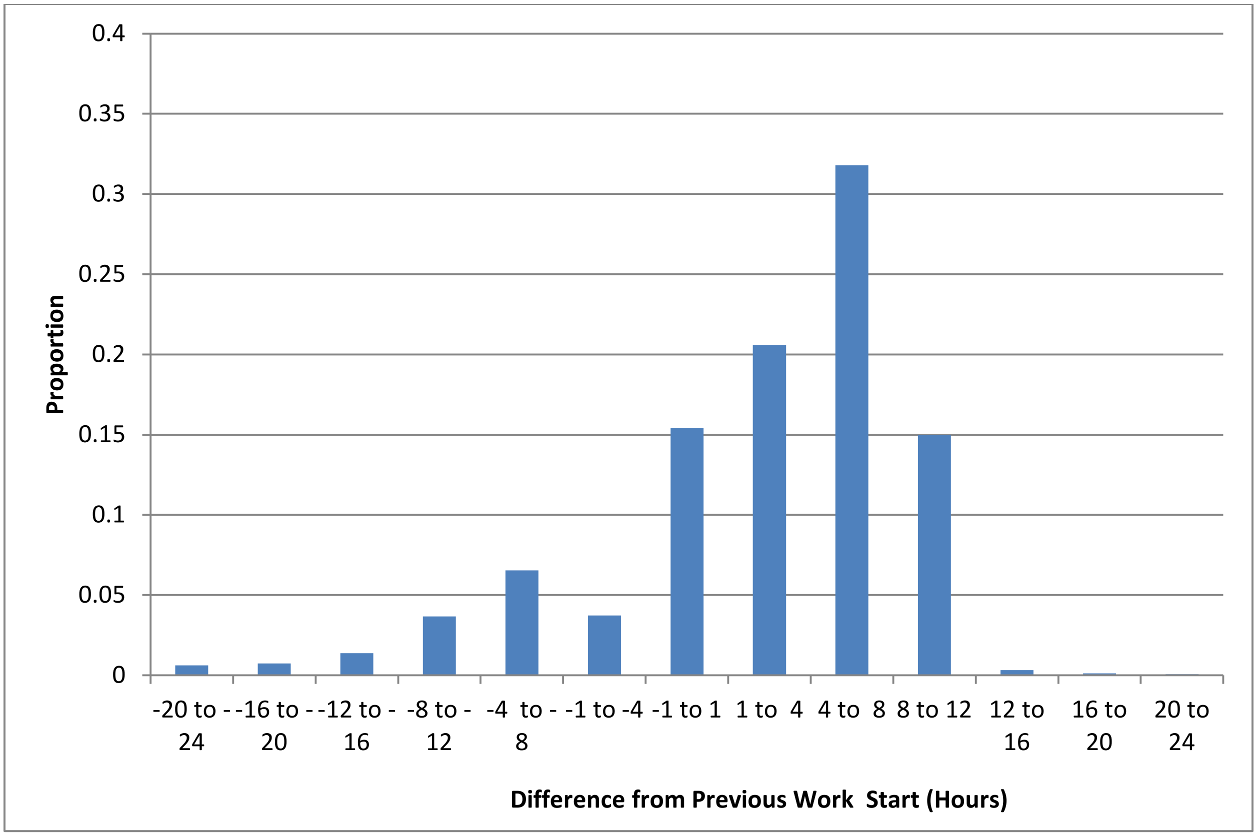

Figure 3. Start time difference distribution for Passenger T&E.

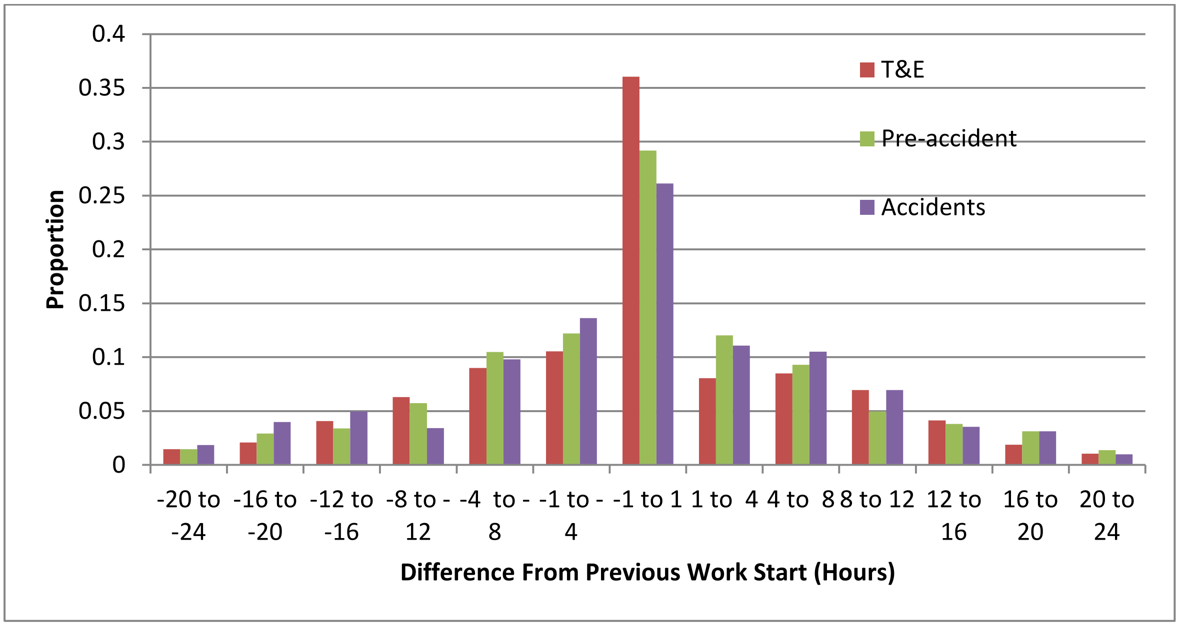

Figure 4. Start time difference distributions for Accidents, Pre-accident, and T&E.

3.2 Statistical Characterization

Figure 5 shows the means and 99 percent confidence intervals for the four distributions. It is clear that the means for Accidents, Pre-accident, and T&E are not statistically different, and the 99 percent confidence intervals include 0 hours start time difference for each distribution. The mean for Passenger T&E is statistically different from the other distributions. The modal start time difference for Passenger T&E was 4–8 hours (see Figure 3), but the mean is 2.75 hours. This finding is consistent with the observation by Gertler and DiFiore (2011) that some passenger T&E employees worked a mix of straight through (fixed start times) and split shifts. Gertler and DiFiore categorized individual passenger T&E employees' work schedules as straight through, split shift, or extra board on the basis of the most frequent type of schedule. Consequently, the distribution of work start time differences for this group reflects a mix of schedules with fixed start times, split shifts with a typical interim release time of 4 hours, and extra board assignments with variable start times and split shifts.

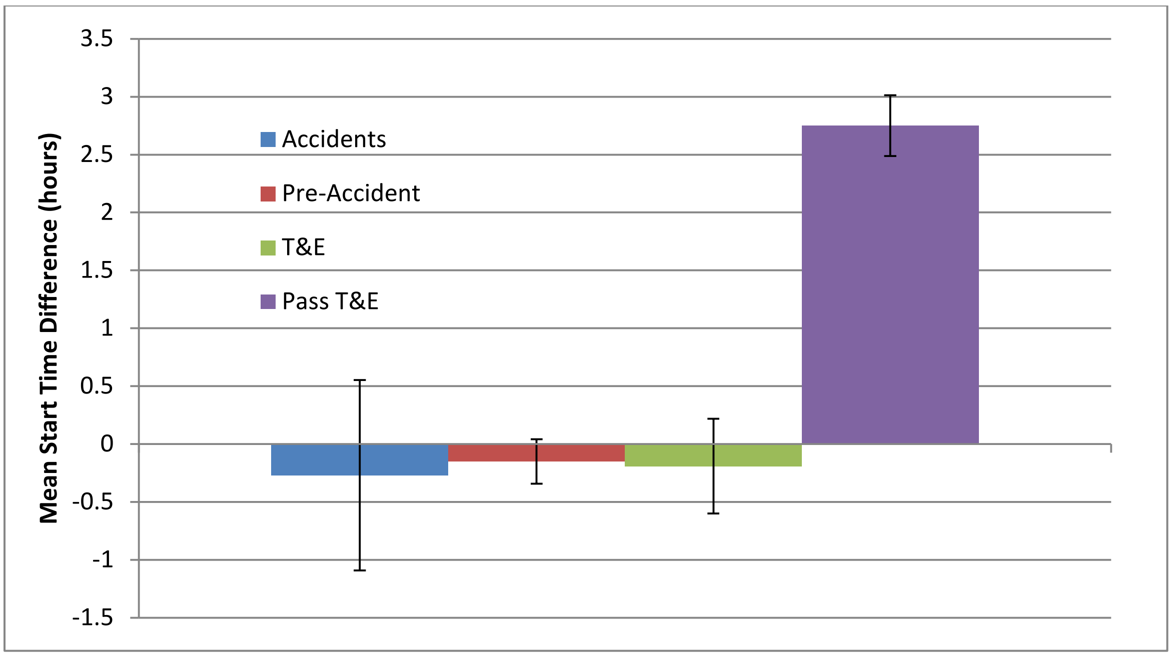

Figure 5. Means and 99% confidence intervals for the distributions.

Figure 6 shows the variances for the four distributions. As was hypothesized, $\sigma^2_{\text{Accidents}} > \sigma^2_{\text{Pre-accident}} > \sigma^2_{\text{T\&E}} > \sigma^2_{\text{Passenger T\&E}}$. Statistically, $\sigma^2_{\text{Accidents}} > \sigma^2_{\text{Pre-accident}}$ ($F_{703,\,11875} = 1.09$, $p < 0.05$); $\sigma^2_{\text{Pre-accident}} > \sigma^2_{\text{T\&E}}$ ($F_{11876,\,2411} = 1.08$, $p < 0.05$); and $\sigma^2_{\text{T\&E}} > \sigma^2_{\text{Passenger T\&E}}$ ($F_{2411,\,3347} = 1.74$, $p < 0.05$). The largest difference in variances was between T&E and Passenger T&E distributions. This is consistent with the picture presented by the whole distributions, as seen in Figures 2–4.

Table 2 presents a statistical summary of the four distributions, including sample sizes (N), means (μ), 99 percent confidence intervals for the means (CI), variances (σ^2), standard deviations (σ), and coefficients of variation (CV).

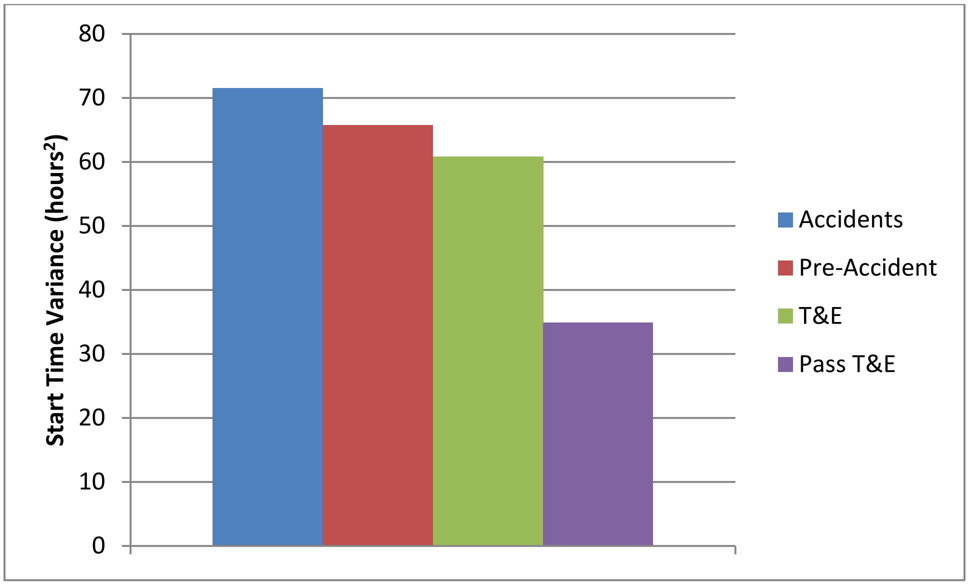

Figure 6. Start time variances.

Table 2. Statistical summary of the Accident, Pre-accident, T&E, and Passenger T&E distributions.

Distribution	N	μ (h)	99% CI (h)	σ^2 (h^2)	σ (h)	CV
Freight T&E, Day of Accidents	704	-0.27	$-1.09 \leq \mu \leq 0.55$	71.52	8.46	-31.32
Freight T&E, Days Preceding Accidents	11,876	-0.15	$-0.34 \leq \mu \leq 0.04$	65.74	8.11	-54.05
T&E (93% Freight), Days without Accidents	2,412	-0.19	$-0.6 \leq \mu \leq 0.22$	60.85	7.80	-41.06
Passenger T&E, Days without Accidents	3,347	2.75	$2.49 \leq \mu \leq 3.01$	34.89	5.91	2.15

3.3 Hazard Functions

It was noted above that it might be possible to characterize each of the Accident, Pre-accident, and T&E distributions as two exponential distributions. One exponential would model the negative side of the distribution, and another exponential would model the positive side. Exponentials are very interesting in this application because the hazard (failure rate) function of an exponential distribution is constant. The hazard function indicates the predictability of future events (the next start time in this case) as a function of elapsed time. If start time differences are distributed exponentially, then knowing the last work start does not reduce uncertainty about the next work start. The time of the next work start would be random. Predictability in an exponential is zero.

Six exponential equations were fit to the Accident, Pre-accident, and T&E distributions. Figure 7 shows the modeled data as a function of the observed data. The red diagonal line shows the outcome if the modeled data is a perfect fit to the observed data. It is clear that the exponential models over-estimate and under-estimate some of the data. The mean r^2 for the six models was 0.9186 (a range of 0.8620 to 0.9569).

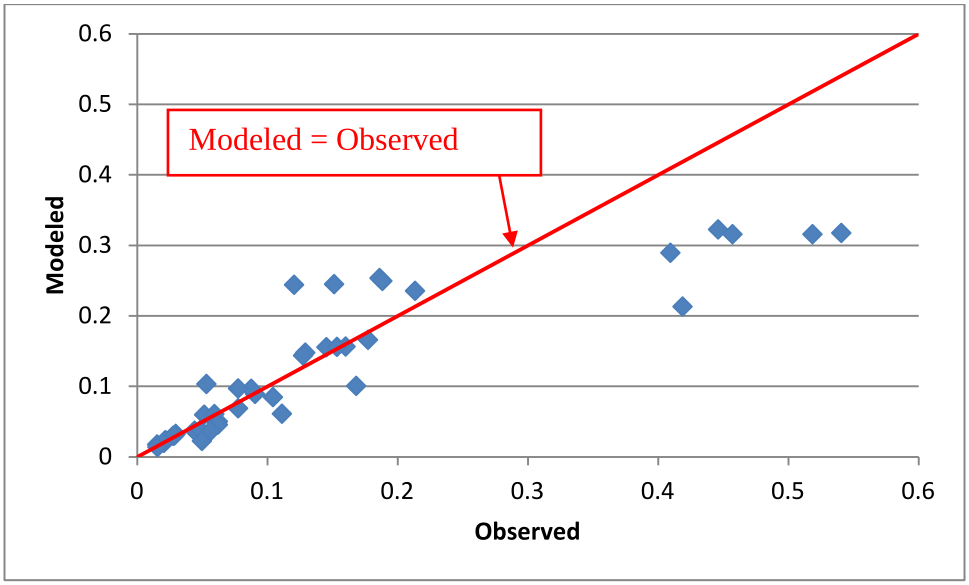

Figure 7. Plot of exponentially modeled data vs. observed data.

Figure 8 shows the residuals for the six models. The residual analysis indicates that there is over-estimation in the -1 to -4 (-2 midpoint) and 1 to 4 (2 midpoint) hour bins and under-estimation in the -1 to 1 hour bin (0 midpoint). χ^2 analyses indicate poor fits in every case to exponential distributions. Table 3 shows the results of these analyses.

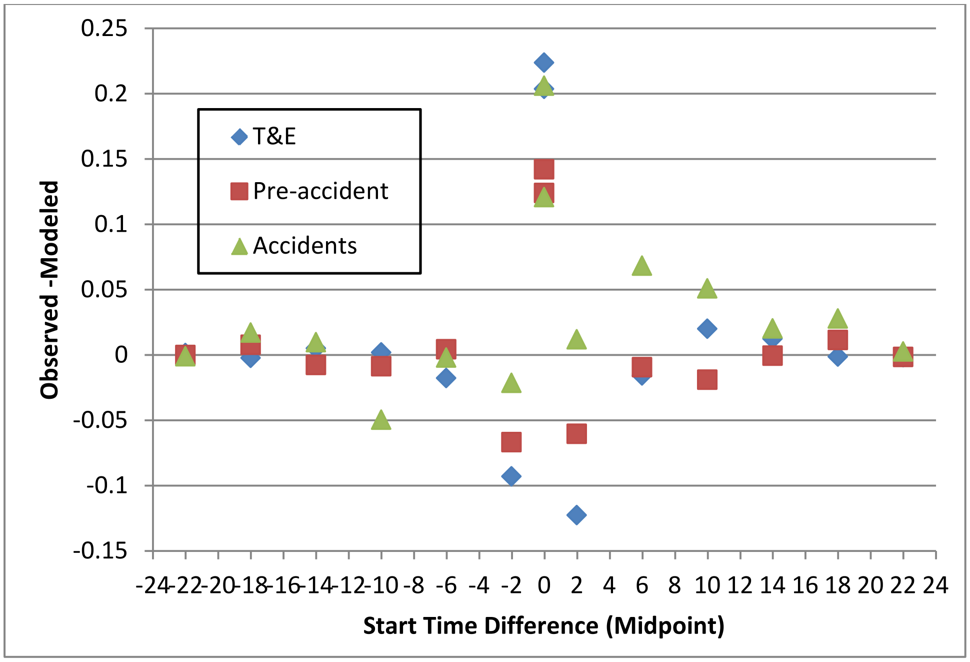

Figure 8. Residuals for the exponential models.

Table 3. χ^2 Analyses of Goodness of Fit to Exponential Distributions†.

	χ^2
Accident +	24.9
Accident -	37.83
Pre-accident +	654.88
Pre-accident -	534.74
T&E +	368.71
T&E -	284.32

† For all tests, df =12, critical value = 21.06, $p<0.05$

3.3.1 Mathematics of hazard functions

Hazard (failure rate) functions were determined for each of the empirical distributions. Hazard is the tendency for an event to occur (this discussion of hazard is based on Luce, 1986, and Kumamoto and Henley, 1996). Suppose an event must occur at one of four times,

$t_0 < t_1 < t_2 < t_3$, and the probability of an event at each time is $p_0 = p_1 = p_2 = p_3 = ¼$. This represents the pdf and is a rectangular distribution. Prior to t_0 the tendency is ¼. If the event fails to occur at t_0, the tendency increases to ⅓ because t_1, t_2, and t_3 are equally likely to occur. If the event fails to occur at t_1, the tendency is ½. If the event fails to occur at t_2, the tendency = 1. Mathematically, the hazard function is

$$\frac{pdf}{1 - cdf}$$

In the case of a rectangular distribution, the pdf = 1/(n+1) = ¼ and the cdf = (x+1)/(n+1). Table 4 shows the calculations.

Table 4. Hazard calculation for a rectangular distribution.

	pdf	cdf	1-cdf (survival)	hazard
t_0	¼	¼	¾	⅓
t_1	¼	½	½	½
t_2	¼	¾	¼	1
t_3	¼	1	0	

Death provides a good, concrete illustration of hazard because the tendency to die increases with age after a certain age and has other characteristics that are typical of hazard functions. Figure 9 shows the pdf for death as a function of age in years. The mean of this distribution is 58.36 years.

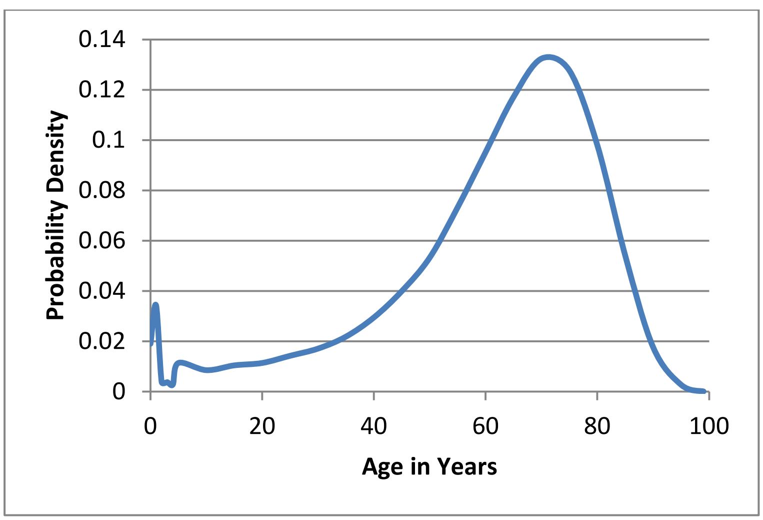

Figure 9. The probability density function for death as a function of age.

Figure 10 shows the survival function (1 – cdf).

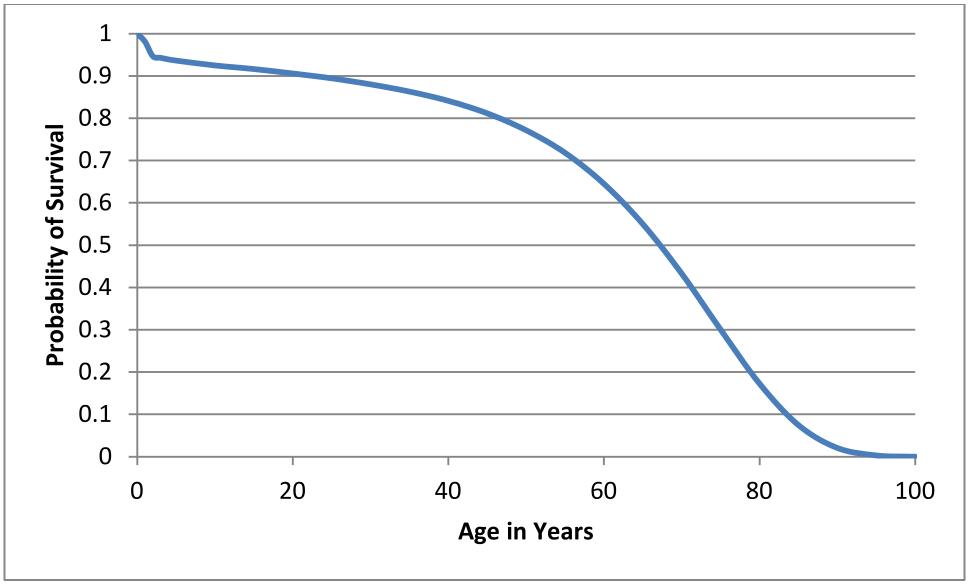

Figure 10. Survival function for death.

Figure 11 shows the hazard function, which is the pdf/(1-cdf) or Figure 9 divided by Figure 10.

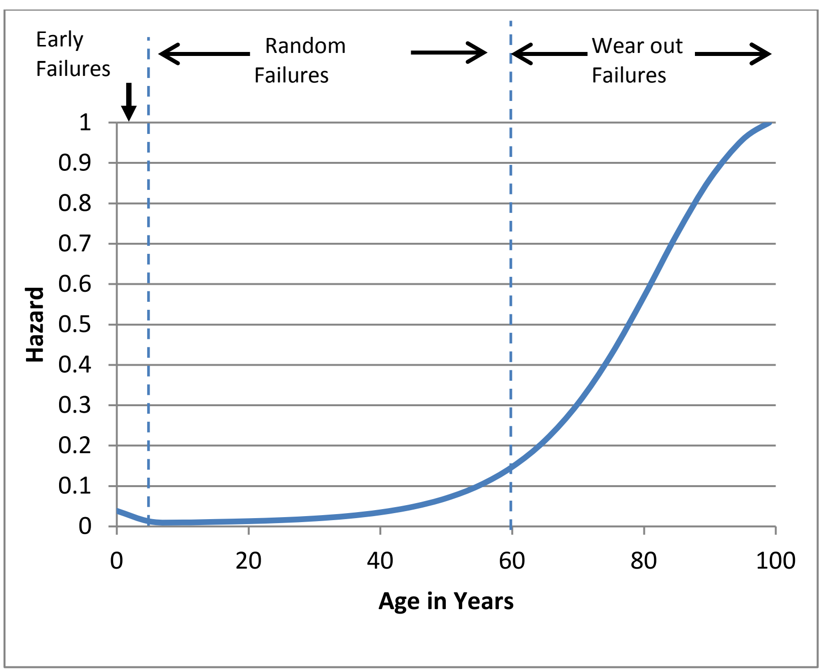

Figure 11. The hazard function for death based on Figures 9 and 10.

Figure 11 has three distinct sections which are often found in hazard functions: early failures, random failures, and wear-out failures. In the case of death, early failures constitute early deaths due to congenital conditions and other risks associated with infancy. Random failures constitute a prime-of-life period in which deaths occur randomly at a low level. Wear-out failures are the result of aging taking an increasing toll on health.

3.3.2 Empirical hazard functions

Figure 12 shows the empirical hazard functions for the Accident, Pre-accident, T&E, and Passenger T&E distributions. All functions have a mode in the -1 to 1 hour bin. This indicates a high tendency for the next work start to occur at the same time of day as the previous work start. That tendency is greatest for T&E, followed by Passenger T&E, Pre-accident, and then Accidents. All functions increase from 0 in the -8 to -12 hour bin, but the Passenger T&E function is higher at this point and remains so through to the -1 to -4 hour bin. In bins above the mode, all functions have an increasing trend, with the exception of the Passenger T&E function. For the Passenger T&E function, there is a drop in the 1 to 4 hour bin, perhaps because interim release is usually 4 or more hours, followed by four bins in which the function looks flat. Overall, the hazard functions indicate more predictability for the Passenger T&E start times relative to the other groups. The reversal in the ordering of the groups at the mode (Passenger T&E is below T&E) is probably due to the higher hazard (predictability) generally seen before and after the -1 to 1 hour bin.

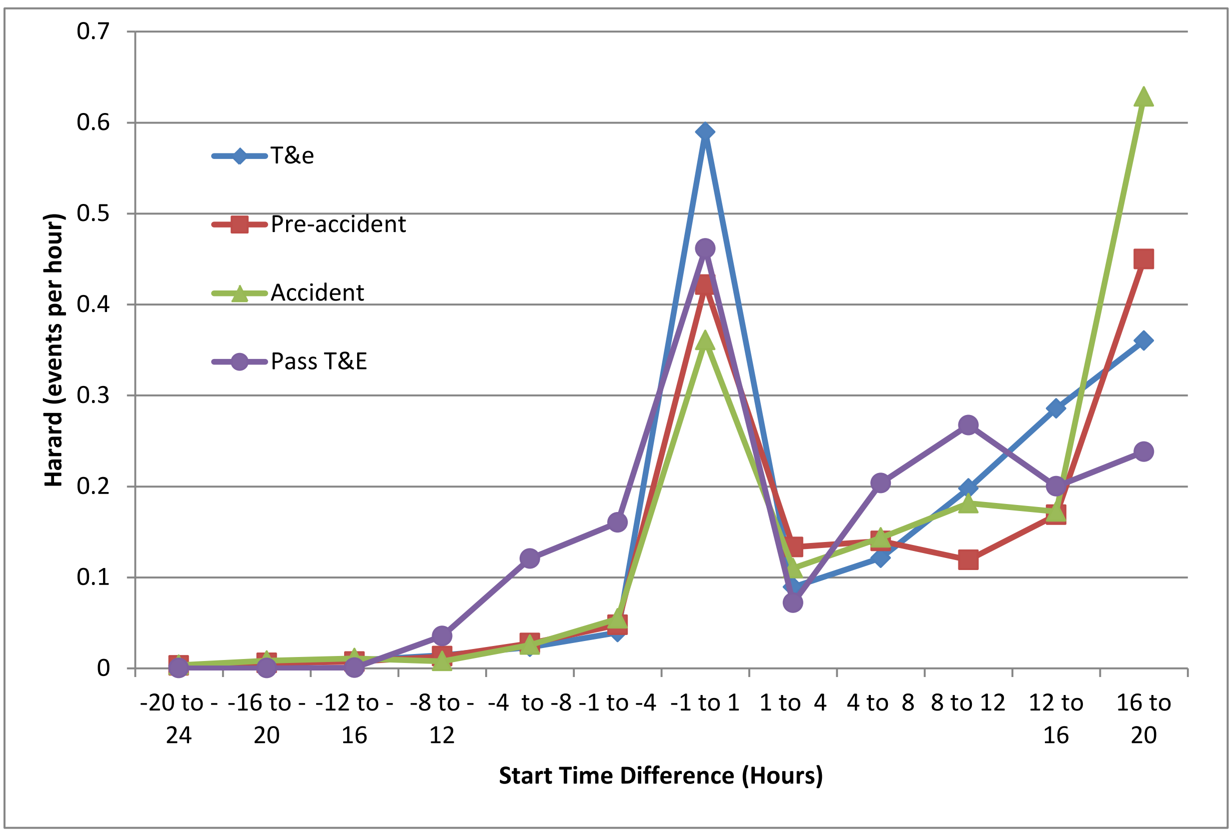

Figure 12. Hazard functions.

3.4 Fatigue and Start Time Variability

One of the assumptions made in predicting the variances of the start time distributions was that fatigue was a function of start time variability. The Work Schedules and Sleep Patterns of Train and Engine Service Workers, the Work Schedules and Sleep Patterns of Passenger Train and Engine Service Workers, and the FAV databases were previously analyzed with FAST to determine the fatigue levels of the involved employees.

Gertler et al. (2013) summarize the results of those analyses in Table 22 of their report. FAST estimates fatigue from a minimum of 3 days of work schedules, so it is not possible to estimate fatigue for Accidents and for Pre-accident separately. The same estimate of fatigue was therefore used for Accidents and Pre-accident. Figure 13 shows the relationship between σ and fatigue (% of work time at a FAST score ≤ 90). A FAST score > 90 indicates that individuals are well-rested. A FAST score ≤ 90 indicates the presence of fatigue.

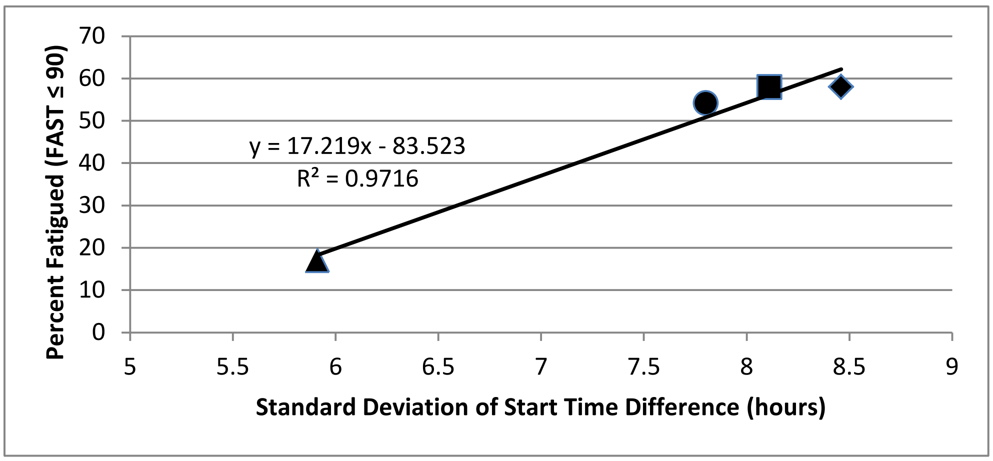

Figure 13. Percent fatigued as a function of the standard deviation of the start time difference. ◆Accident, ■ Pre-accident, ●T&E, ▲ Passenger T&E.

Figure 13 shows that fatigue for Passenger T&E < T&E < Pre-accident = Accidents. The correlation is 0.9857 ($p < 0.05$). It is clear that fatigue increases as start time variability increases. Fatigue is known to increase the probability of accidents (Raslear et al., 2011) and is the intervening variable that mediates the relationship between start time variability and accidents.

4. Discussion and Conclusions

This report describes two measures of variability or predictability of work start times: the variance (σ^2) and the hazard function. Each can play a role in the analysis of start time predictability. σ^2 is an excellent measure for assessing the overall start time variability of a group of work schedules and for comparing different groups of work schedules[2]. For instance, in the case of freight T&E and passenger T&E, σ^2 indicated that passenger T&E schedules had significantly greater predictability relative to freight T&E schedules. The hazard function is useful for specifying the location of such predictability. Again, looking at freight versus passenger T&E, freight T&E has the highest predictability in the -1 to 1 hour bin. Passenger T&E has less predictability in the -1 to 1 hour bin, but has a higher likelihood of a start time 8 to 1 hour(s) before the previous work start. This type of information, combined with knowledge of the operational circumstances, can support evidence-based decisions about schedule changes that effectively reduce fatigue without adversely affecting operations.

The variance data supported the hypothesis that the probability of a human factors accident is a function of start time variability (equation 5). Fatigue, as measured by the FAST score, was also shown to be a function of start time variability. While it was previously demonstrated that fatigue was a general function of sleep and work schedules (Raslear et al., 2011), this report extends that finding to specify start time variability as a critical aspect of work schedules when considering fatigue and the probability of an accident.

4.1 Conclusions

1. The variance and hazard functions are useful measures of work start time predictability. Each has a different role in start time analysis. The variance is useful for comparing the overall start time variability of several groups of schedules. The hazard function is useful for specifying the location of predictability in a group of schedules.

2. As predicted, $\sigma^2_{\mathrm{Accidents}} \geq \sigma^2_{\mathrm{Pre-accident}} > \sigma^2_{\mathrm{T\&}E} > \sigma^2_{\mathrm{Passenger\ T\&}E}$. This ordering of variances supports the hypothesis that the probability of a human factors accident is a function of start time variability.

[2] It should be noted that the variance should not be used as a predictor of fatigue in work schedules that consist primarily of night work. For instance, dispatchers who work third shift have highly predictable schedules but are also highly fatigued (Gertler et al., 2013). This is because normal circadian rhythms interfere with sleep during the daytime.

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