Accident Analysis and Prevention 126 (2019) 142–145

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

Predicting performance and safety based on driver fatigue

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ARTICLE INFO

Keywords:
Circadian rhythm
Sleep loss
Drowsy driving
Fatigue risk management
Biomathematical fatigue model
Hard-braking events

ABSTRACT

Fatigue causes decrements in vigilant attention and reaction time and is a major safety hazard in the trucking industry. There is a need to quantify the relationship between driver fatigue and safety in terms of operationally relevant measures. Hard-braking events are a suitable measure for this purpose as they are relatively easily observed and are correlated with collisions and near-crashes. We developed an analytic approach that predicts driver fatigue based on a biomathematical model and then estimates hard-braking events as a function of predicted fatigue, controlling for time of day to account for systematic variations in exposure (traffic density). The analysis used de-identified data from a previously published, naturalistic field study of 106 U.S. commercial motor vehicle (CMV) drivers. Data analyzed included drivers' official duty logs, sleep patterns measured around the clock using wrist actigraphy, and continuous recording of vehicle data to capture hard-braking events. The curve relating predicted fatigue to hard-braking events showed that the frequency of hard-braking events increased as predicted fatigue levels worsened. For each increment on the fatigue scale, the frequency of hard-braking events increased by 7.8%. The results provide proof of concept for a novel approach that predicts fatigue based on drivers' sleep patterns and estimates driving performance in terms of an operational metric related to safety. The approach can be translated to practice by CMV operators to achieve a fatigue risk profile specific to their own settings, in order to support data-driven decisions about fatigue countermeasures that cost-effectively deliver quantifiable operational benefits.

1. Introduction

Fatigue is a major safety hazard in the trucking industry (Philip and Åkerstedt, 2006). There are many factors that contribute to driver fatigue such as long working hours, night and early morning duty periods, and chronic sleep insufficiency (Van Dongen et al., 2003; Mollicone et al., 2010). Regardless of its cause, fatigue causes decrements in vigilant attention and reaction time (Lim and Dinges, 2008), impacting safety (Van Dongen et al., 2016).

There is a need to better understand the relationship between driver fatigue and safety (Williamson et al., 2011; Sparrow and Van Dongen, accepted). Metrics already being collected by commercial motor vehicle (CMV) operators may offer a practical means of quantifying this relationship. One readily available metric is hard braking (Dinges et al., 2017). Hard-braking events are safety-critical events that are highly correlated with collisions and near-crashes (Dingus et al., 2006).

Models that account for the effects of sleep/wake and circadian factors that drive fatigue (Hursh et al., 2016; Calabrese et al., 2017) can be used to predict fatigue risk levels for given work/rest schedules (Dawson et al., 2011). A number of biomathematical models (e.g., Åkerstedt and Folkard, 1997; Jewett and Kronauer, 1999; Hursh et al., 2004; McCauley et al., 2013) have been proposed to predict fatigue risk based on the neurobiology of sleep/wake regulation. These models differ based on factors such as the range of sleep/wake schedules considered and the fatigue measures used to fit the model.

In the present study, we used a biomathematical fatigue model (McCauley et al., 2009, 2013) fit to data from three laboratory studies with total or partial sleep deprivation, with and without naps, or simulated night shift work, and validated against data from three separate laboratory studies with total sleep deprivation, with and without naps, or partial sleep deprivation followed by varying doses of recovery sleep. The model provides a fatigue score that is calibrated to performance lapses on the Psychomotor Vigilance Test (PVT), a 10-min reaction time task that measures behavioral alertness (Lim and Dinges,

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https://doi.org/10.1016/j.aap.2018.03.004
Received 31 August 2017; Received in revised form 27 February 2018; Accepted 2 March 2018
Available online 03 April 2018

2008). For reference, for a schedule with 8 h of sleep per night the model predicts a daytime average of 4.6 lapses on the PVT, while after 24 h awake it predicts 16.5 lapses.

Model-based fatigue predictions have already been used to account for human factors-related incident rates in rail operations (Hursh et al., 2011). Here we focused on CMV operations, and developed an analytic approach that applied a biomathematical fatigue model (McCauley et al., 2013) to individual driver sleep/wake timelines and the occurrence of hard-braking events as a proxy for human factors-related incident rates. We derived a curve that expresses the occurrence of hard-braking events as a function of the predicted fatigue level, in combination with a time-of-day factor to account for exposure (daily traffic density fluctuations). This curve could be used in operational settings to predict risk for the occurrence of safety critical-events and take mitigating steps to avoid them.

We performed our analysis with data from a previously published naturalistic field study, where drivers performed their normal duties and managed their schedules without any interventions. The study is described in detail in an earlier publication in this journal (Sparrow et al., 2016). Our objective was to develop a quantitative resource to enable CMV operators to make data-driven decisions about fatigue countermeasures that are cost-effective and deliver quantifiable operational benefits.

2. Methods

2.1. Participants

The study population consisted of truck drivers utilizing the U.S. hours of service (HOS) restart provision, which allows drivers to reset their duty clock by taking a 34-h restart break. Participating drivers were required to be fit for duty by regulatory standards and possess a valid commercial driver's license. A total of $N = 106$ drivers completed the study (Sparrow et al., 2016), including 100 men and 6 women, ranging in age from 24 to 69 years (mean ± SD: 45.4 ± 10.7 years). Study participants reported having up to 39 years of experience as a CMV driver (mean ± SD: 12.4 ± 8.7 years). Three drivers were owner-operators independently contracting with a carrier. The remainder were employees of one of three different carriers. These drivers had been employed by their current carrier for up to 25 years (mean ± SD: 6.3 ± 6.4 years). The sample consisted of 44 local drivers, 26 regional drivers, and 36 over-the-road (long-distance) drivers. No collisions occurred during the study.

All drivers gave written, informed consent. Drivers were compensated for their study participation. They were informed that their participation in the study would not affect their employment or contractual relationship with their carrier, and that their data would be kept strictly confidential. Data were de-identified prior to analysis. Data were protected from disclosure by means of a Certificate of Confidentiality issued by the National Institutes of Health. The study protocol was approved by the Institutional Review Board of Washington State University.

2.2. Measurements

Data were collected from all 106 drivers (Sparrow et al., 2016). The average duration of study participation was 11.9 days (SD: 1.5 days). Data covered 1260 duty days, capturing 414,937 miles (8049 h) of driving. The study included measures of duty status (continuously monitored via electronic logging device), sleep (continuously monitored via wrist-worn actigraph), psychomotor vigilance performance (measured through testing on a 3-min performance task three times a day), self-reported sleepiness (recorded three times a day), and driving performance (continuously monitored via vehicle data acquisition systems while the truck's ignition switch was activated). The current analysis focuses on a subset of these measures: duty status, sleep, and the frequency of hard-braking events.

2.2.1. Duty status

Drivers' official duty logs for the period of the study were downloaded from their carriers' duty log databases. From each driver's duty log, on-duty status and driving status were extracted in 1-min intervals. For proper alignment of data sets, all data were expressed in terms of each driver's home terminal time zone.

2.2.2. Sleep

Drivers were provided with a wrist-worn actigraph (Actiwatch 2; Philips Respironics, Bend, OR), which they were asked to wear continuously throughout the study to measure sleep/wake patterns. The actigraph recorded cumulative activity (movement) counts in 1-min intervals. Sleep/wake times were scored using a validated, automated scoring algorithm (Actiware 6; Philips Respironics, Bend, OR).

2.2.3. Hard-braking events

For the duration of the study, participating drivers were assigned a study vehicle of the type they were driving routinely – either a Freightliner Cascadia (82 drivers) or an International ProStar (24 drivers). Study vehicles were equipped with a data acquisition system (Pulsar Informatics, Philadelphia, PA), which made continuous, passive recordings while the vehicle was in use (i.e., when the ignition switch was activated). The data acquisition system recorded distance traveled, speed, fuel use, and a range of other vehicle-based parameters and driving metrics. The system also captured hard-braking events, derived from vehicle speed data retrieved from the SAE J1939 network through a controller area network (CAN) bus; and acceleration, derived from a global positioning system (GPS) device based on 1-second forward differences of the speed observations (sampled at 10 Hz). A hard-braking event was defined by a deceleration force greater than 0.3 g. Recorded data were encrypted and transmitted to a secure computer server via cellular networks. A grand total of 7320 h out of a possible 8049 h (90.9%) of driving data was captured by the vehicle data acquisition systems.

2.3. Analytic approach

An analysis was performed by (1) assessing driver fatigue as predicted from the actigraphically scored sleep/wake patterns using a biomathematical model (McCauley et al., 2013); (2) quantifying driver performance in terms of hard-braking events; and (3) fitting a generalized linear statistical model to estimate the relationship between predicted fatigue and hard-braking events. Using this statistical model, risk estimates of hard-braking events were made for the entire timeline of each subject in the study based on their scored sleep/wake history.

Each subject's study timeline was segmented into 60-min intervals and a fatigue value was assigned to each interval based on the prediction from the biomathematical model at the interval start time. Within each 60-min interval, the drive duration (e.g., 60 min if driving continuously, or less than 60 min if breaks were taken or non-driving duty tasks were performed during the interval) was recorded and the number of hard-braking events was counted based on the presence of decelerations greater than 0.3 g when traveling at over 30 mph.

A generalized linear modeling approach (McCullagh, 1984) was used to estimate the relationship between predicted fatigue and the observed rate of hard-braking events. Although the fatigue model includes a fixed circadian component (McCauley et al., 2013), an additional time-of-day factor was included to account for systematic time-of-day variations in exposure (traffic density).

Within each 60-min interval, the number of hard-braking events, n, was modeled based on a Poisson distribution with an average number of events, μ:

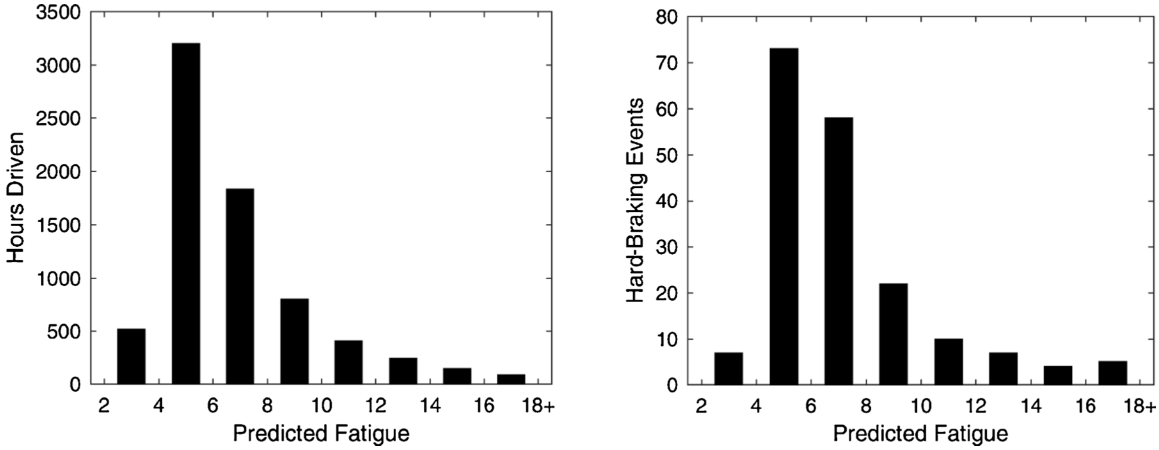

Fig. 1. Distributions of hours driven and hard-braking events by predicted fatigue score.

$$P(n) = \frac{\mu^n e^{-\mu}}{n!}.$$

The rate of events, λ, was modeled based on a Poisson log-linear regression model of explanatory factors, x_i, with regression coefficients, β_i:

$$\lambda = \exp\left(\beta_0 + \sum_{i=1}^{m} \beta_i x_i\right),$$

where m is the number of explanatory factors (see below). Substituting $\lambda = \mu/T$, where T is the time driven within each interval, the number of events within each interval can be estimated as:

$$\log \mu = \beta_0 + \sum_{i=1}^{m} \beta_i x_i + \log T.$$

By subtracting $\log T$ from both sides of the equation, it can be viewed as a model of the hard-braking rate, ρ:

$$\log \rho = \log \frac{\mu}{T} = \beta_0 + \sum_{i=1}^{m} \beta_i x_i.$$

The first explanatory factor in this model, x_1, was designated to represent predicted fatigue (parameter β_1) as derived from the bio-mathematical model (McCauley et al., 2013). The relationship between x_1 and ρ takes the form of an exponential curve. Further explanatory factors were designated to represent exposure (traffic density). While exposure was not measured directly, a function of time of day was used that could capture daily exposure changes during, for example, the morning and evening rush hours. This function f was selected to be a sinusoid with a fundamental period of 24 ho and its two harmonics, with unknown phases φ and amplitudes A:

$$f(t) = \sum_{j=1}^{3} A_j \sin\left(\frac{2\pi jt}{24} + \varphi_j\right),$$

where t is time of day. This function can be linearized, as follows:

$$f(t) = \sum_{j=1}^{3} \beta_{2j} \sin\left(\frac{2\pi j\, t}{24}\right) + \beta_{2j+1} \cos\left(\frac{2\pi j\, t}{24}\right).$$

By defining $x_{2j} = \sin\left(\frac{2\pi j\, t}{24}\right)$ and $x_{2j+1} = \cos\left(\frac{2\pi j\, t}{24}\right)$, this can be simplified to:

$$f(t) = \sum_{i=2}^{7} \beta_i x_i,$$

which can be readily included in the regression model defined above. The regression model as a whole therefore has $m = 7$ predictor variables.

It should be noted that use of a Poisson model assumes that the mean and variance of the rate parameter are equal. When the mean is less than the variance, the data is overdispersed, and when the mean is greater than the variance, the data is underdispersed. The overall mean and variance of the number of events per interval were 0.0173 and 0.0186, respectively. For the model fitted here, the estimated dispersion was 1.3, and overdispersion was not judged to be a significant issue.

Finally, relative risk (*RR*) was calculated from the regression model by selecting a reference fatigue level, x_0, for comparison. Keeping all other factors fixed, *RR* was calculated as follows:

$$RR = \frac{\rho(x_1 = x)}{\rho(x_1 = x_0)} = \frac{\exp(\beta_0 + \beta_1 x + \sum_{i=2}^{7} \beta_i x_i)}{\exp(\beta_0 + \beta_1 x_0 + \sum_{i=2}^{7} \beta_i x_i)} = \exp(\beta_1 (x - x_0)).$$

3. Results and discussion

Of the 7320 h of driving captured by the vehicle data acquisition system, 50% were associated with predicted fatigue scores of 5.9 (median fatigue score) or greater; 5% were associated with predicted fatigue scores of 12.75 or greater; and 1% were associated with predicted fatigue scores of 16.5 or greater. See Fig. 1a. A total of 186 hard-braking events were recorded during the study. See Fig. 1b. By contrast with hours driving (Fig. 1b), of the 186 hard-braking events in Fig. 1a, 58% were associated with fatigue scores of 5.90 or greater, 5% were associated with fatigue scores of 12.75 or greater, and 2% were associated with fatigue scores of 16.5 or greater.

The frequency of hard-braking events increased as predicted fatigue levels worsened, after accounting for time of day. Based on the Poisson regression model ($F_{7,}$ 10,768 = 2.4, $p = 0.018$), the estimated parameter for the fatigue factor was $\beta_1 = 0.0746$ (SE = 0.0315). This model describes an exponential relationship in which a 1-unit increment on the fatigue scale (i.e., 1 lapse on the PVT) increases the frequency of hard-braking events by 7.8%. The relative risk curve, expressed relative to the median predicted fatigue score of 5.9, is shown in Fig. 2. Based on the model, when driving at a fatigue level of 12.75 (the highest 5% predicted), the risk of having a hard-braking event increases by a factor of 1.66; and when driving at a fatigue level of 16.5 (the highest 1% predicted), the risk increases by a factor of 2.19.

These results, derived from a sample of truck drivers participating in a naturalistic field study, provide proof-of-concept for our approach of predicting fatigue based on drivers' sleep patterns and estimating driving performance in terms of an operational metric related to safety (i.e., hard-braking events). Using this method, we were able to quantitatively express the relationship of predicted fatigue levels based on sleep/wake schedules with the risk of hard-braking events, thereby providing a link between fatigue and a proxy measure of safety. This

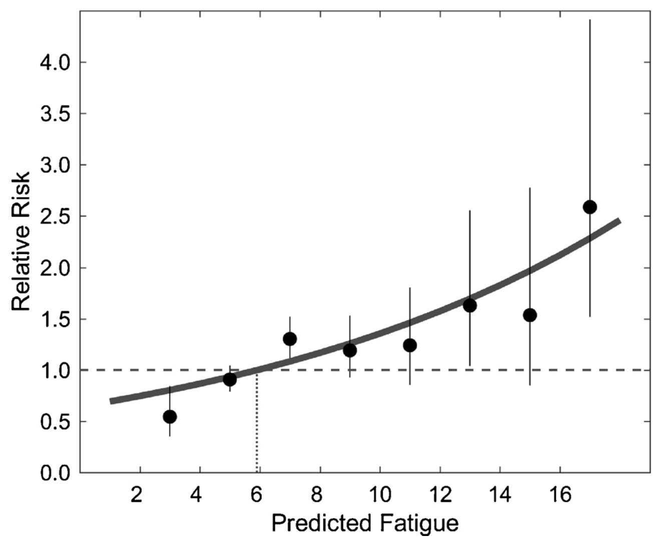

Fig. 2. Relative risk of hard-braking events (accounting for time of day) as a function of predicted fatigue. Risk is expressed relative to the median predicted fatigue level of 5.9 (vertical dotted line), which is chosen as the baseline relative risk of 1 (horizontal dashed line). The thick solid line shows the multiplication factor (fold change) by which risk increases or decreases as a function of predicted fatigue. For example, at a predicted fatigue level of 14, the predicted relative risk of hard-braking events is a 1.8-fold increase. The dots represent the mean relative risk as observed in the study data, after accounting for exposure (time-of-day variations in traffic density), binned by fatigue level (as in Fig. 1). The error bars show the standard error of the mean.

analytic approach can be translated to practice by CMV operators to achieve a fatigue risk profile specific to their own operations, in order to support data-driven decisions about fatigue countermeasures that cost-effectively deliver quantifiable operational benefits. When combined with data linking safety-critical events to accidents, this approach can also be extended to account for the cost of fatigue-related accidents (Hursh et al., 2008, 2011), providing CMV operators with a tool to make a business case for investments in fatigue risk management.

Acknowledgments

This work was supported by the Federal Motor Carrier Safety Administration (FMCSA) under contract DTMC7514D00011. The FMCSA was not involved in writing the paper, and the paper does not necessarily reflect their views.

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