ARTICLE IN PRESS

Accident Analysis and Prevention xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Accident Analysis and Prevention

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

Predicting performance and safety based on driver fatigue

Daniel Mollicone[a,*], Kevin Kan[a], Chris Mott[a], Rachel Bartels[a], Steve Bruneau[a], Matthew van Wollen[a], Amy R. Sparrow[b], Hans P.A. Van Dongen[b]

[a] Pulsar Informatics, Inc., United States
[b] Sleep and Performance Research Center, Washington State University, United States

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,

* Corresponding author at: 1424 Fourth Avenue, Suite 414 Seattle, WA 98101, United States.
E-mail addresses: daniel@pulsarinformatics.com (D. Mollicone), kkan@pulsarinformatics.com (K. Kan), chris@pulsarinformatics.com (C. Mott), rachel@pulsarinformatics.com (R. Bartels), steve@pulsarinformatics.com (S. Bruneau), matthew@pulsarinformatics.com (M. van Wollen), amy.sparrow@wsu.edu (A.R. Sparrow), hvd@wsu.edu (H.P.A. Van Dongen).

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
0001-4575/

Please cite this article as: Mollicone, D., Accident Analysis and Prevention (2018), https://doi.org/10.1016/j.aap.2018.03.004

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: