Modeling Recurrent Safety Critical Events among Commercial Truck Drivers: A Bayesian Hierarchical Jump Power Law Process

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Abstract

Many transportation safety studies aim to predict crashes based on aggregated road segment data. Safety-critical events (SCEs), such as hard brakes or collision mitigation braking, are widely used as proxy measures of driving risk. While there can only be one crash on a driving shift, multiple SCEs can occur in one shift and they do not interrupt the state of driving. We use data from a large naturalistic driving study that includes over 13 million driving records and 8,386 SCEs generated by 496 commercial truck drivers over one year to address two types of questions regarding the safety behavior of commercial truck drivers. First, does the occurrence of SCEs tend to increase during a shift due to fatigue or some other reason? Second, what is the effect of rest breaks on safety behavior? We propose a Bayesian hierarchical non-homogeneous Poisson process with power law process intensity function and a Bayesian hierarchical jump power law process, similar to the kinds of models that are often applied to analyze failure data from repairable systems. We find that the intensity for hard breaks decreases throughout a shift, and rest breaks reduce the likelihood of having to activate the automated collision mitigation system. Properties of the approach are investigated through a simulation study. Supplementary materials including simulated data and code to obtain parameter estimates for reproducing the work, are available as an online supplement.

Keywords: trucking; safety-critical events; reliability; power law process

I. INTRODUCTION

Commercial truck drivers "form the lifeblood of [the U.S.] economy" (The White House, 2020), generating annual revenues exceeding $700 billion from the transportation of 10.8 billion tons of freight (John, 2019). The industry typically requires drivers to be on the road for an extended period of time, incentivizing drivers with hourly, per-mile or per-delivery pay schedules. Furthermore, the industry is heavily regulated through the *hours of service* regulation (Federal Motor Carrier Safety Administration, 2020b), which dictates the total number of driving hours permitted, minimum length of off-duty rest periods and allowable weekly total hours of driving/rest. Consequently, a major difference between commercial (large) truck drivers and commuters is the complex operational environment required of commercial drivers. Specifically, commercial drivers have to abide by government regulations while managing industry practices that attempt to optimize both productivity and safety.

The safety of truck drivers is of critical importance not only to trucking operators, but also to the general public. Truck crashes have a two-fold penalty (Tsai et al., 2018) (a) direct losses arising from injuries, fatalities and property damage affecting the truck driver and other commuters on the road, and (b) indirect losses in efficiency associated with slowing/damaging transferred goods and the impact to travel time for other commuters. Alarmingly, despite the regulatory oversights and continued advancements in safety technologies, the rates of truck-involved crashes in the U.S. have increased over the past decade. The involvement rate per 100 million large-truck miles traveled increased from 1.32 in 2008 to 1.48 in 2016 for fatal crashes, and from 21 in 2008 to 31 in 2015, most recent data, for injury crashes (NHTSA's National Center for Statistics and Analysis, 2019).

Traditional trucking safety studies utilize one or more *road segments* as the unit of analysis (Mehdizadeh et al., 2020) and attempt to model the occurrence or the number of crashes in a fixed time period (Lord and Mannering, 2010; Savolainen et al., 2011; Mannering and Bhat, 2014). Thus, the developed models use/resemble a case-control study design (Mehdizadeh et al., 2020). Limitations of those studies include a small number of observed crashes, difficulty in selecting control groups, and an undercount of less severe crashes (Mehdizadeh et al., 2020). More importantly, those studies cannot capture driver behavioral factors which contribute to 90% of traffic crashes (Federal Highway Administration, 2019).

To address the deficiencies in traditional safety studies, large-scale naturalistic driving studies (NDSs) have received significant attention in recent years (see e.g., Guo, 2019; Mehdizadeh et al., 2020; Cai et al., 2020). Those studies capitalize on advances in communication, computing and on-board vehicular sensing technologies which have allowed for the continuous recording of real-world driving data (e.g., timestamps capturing driving location, speed, rest brakes, etc.). In addition to their ability to capture continuous data on possible explanatory variables, NDSs allow for using more frequent near-crash safety critical events (SCEs) as proxies for crash data. It is well-established that increases in SCEs (e.g., hard braking events or the activation of forward-collision mitigation systems) are positively correlated with crash rates (Dingus et al., 2006; Guo et al., 2010; Gordon et al., 2011; Cai et al., 2020). Consequently, SCEs are the preferred choice for outcome variables in NDSs since they are more frequent (Cai et al., 2020) and hence, provide larger statistical power.

As with most point process data, SCEs can be divided into models attempting to (a) quantify the likelihood of observing one or more SCEs through binary classification (Ghasemzadeh and Ahmed, 2017, 2018) and count data models (Kim et al., 2013), respectively, and (b) estimate the time(s) of observing SCEs (Li et al., 2018; Liu and Guo, 2019; Liu et al., 2019; Guo et al., 2019). Three major limitations are inherent with these modeling approaches. First, NDSs follow drivers/vehicles for an extended time period, i.e., their application resembles a prospective cohort study (Mehdizadeh et al., 2020). However, much of the existing literature utilize methodologies of case-control studies to this type of data by including all events and match them with selective non-events (e.g., Ghasemzadeh and Ahmed, 2018; Das et al., 2019), which reduces the statistical power to detect potentially existing effects and fails to account for the fact that the driving data are nested within drivers. Second, the occurrence of multiple SCEs in an extended time period is not unusual. Therefore, binary classification models are inefficient since they cannot distinguish between cases where one or more SCEs occur. Furthermore, count models fail to consider the time stamps associated with each SCE, which is a critical factor in designing interventions in practice. Third, based on the *hours of service* regulation, breaks are required for intermediate and long trips. The underlying hypothesis/rationale is that these breaks would improve the driver's safety performance, which cannot be modeled using existing methodologies.

Owing to the three identified gaps in NDS models, the overarching motivation of this paper is to examine how large NDS datasets can be modeled to account for both the timing of an observed event and the effect of rest breaks on SCE occurence. This study is performed in collaboration with a leading shipping freight company in the U.S. The collaboration with industry provides the following unique settings: (a) the company's fleet used a commercially available driving events monitoring system, which meant that the SCE data were collected routinely as a part of the fleet's operations; (b) the truck drivers included in this study were all employed by the company at the time of data collection, i.e., a consistent operational and safety policy governs the drivers' behavior; and (c) the routes chosen by the drivers are subject to company policies, delivery windows and government regulations, i.e., naturally follow realistic commercial driving patterns. Based on this setup, we have naturalistic driving data generated by 496 regional commercial large-truck drivers, capturing over 20 million miles driven and over 8,300 SCEs. Note that existing trucking NDS datasets are much smaller, with largest reported values of approximately 200 drivers (Federal Motor Carrier Safety Administration, 2020a) and 0.414 million miles driven (Sparrow et al., 2016). Thus, this study can overcome the small sample sizes and limited driving locations in previous NDSs.

In this article, we address two types of questions regarding the safety behavior of commercial truck drivers. First, does the occurrence of SCEs tend to increase during a shift (a continuous period for which the driver is on duty, but not necessarily driving), due to fatigue or some other reason? If so, how is this effect manifested, and for which type of SCE does this occur? Second, what is the effect of rest breaks on driving safety performance? To what extent does safety change after a rest break? In order to facilitate the modeling of these two sets of questions, we introduce and capitalize on the following analogy:

- The first set of questions can be considered as a degradation process, where continued driving results in a degraded safety performance similar to continued operation degrades a process/system in the field of *reliability*.
- Building on the analogy, a rest-break can be considered as a preventive maintenance activity, which can be either time-based (e.g., every two hours) or condition-based (e.g., if a driver stops for coffee to increase their alertness). The *maintenance* act improves the driver's reliability by reducing the degradation, which we hypothesize to reduce the likelihood of an SCE if the occurrence of an SCE is not arbitrary.

- A potential difference between a product and a driver's reliability is that products of similar vintage are typically assumed to be homogeneous. On the other hand, the modeling of drivers should be personalized (i.e., assuming heterogeneity of the sampling units), which can be accounted for using hierarchical modeling approaches.

With the research questions and analogy in mind, we introduce a Bayesian hierarchical non-homogeneous Poisson process with the power law process (PLP) intensity function to model SCEs within shifts. This model can account for driver-level unobserved heterogeneity by specifying driver-level random intercepts for the rate parameter in PLP. On the other hand, to account for the feature that multiple breaks are nested within a shift among commercial truck drivers, we then propose a Bayesian hierarchical jump power law process (JPLP) to take potential reliability changes at the time of rests into consideration. Figure 1 presents an illustration of using PLP and JPLP in modeling the intensity function of SCEs.

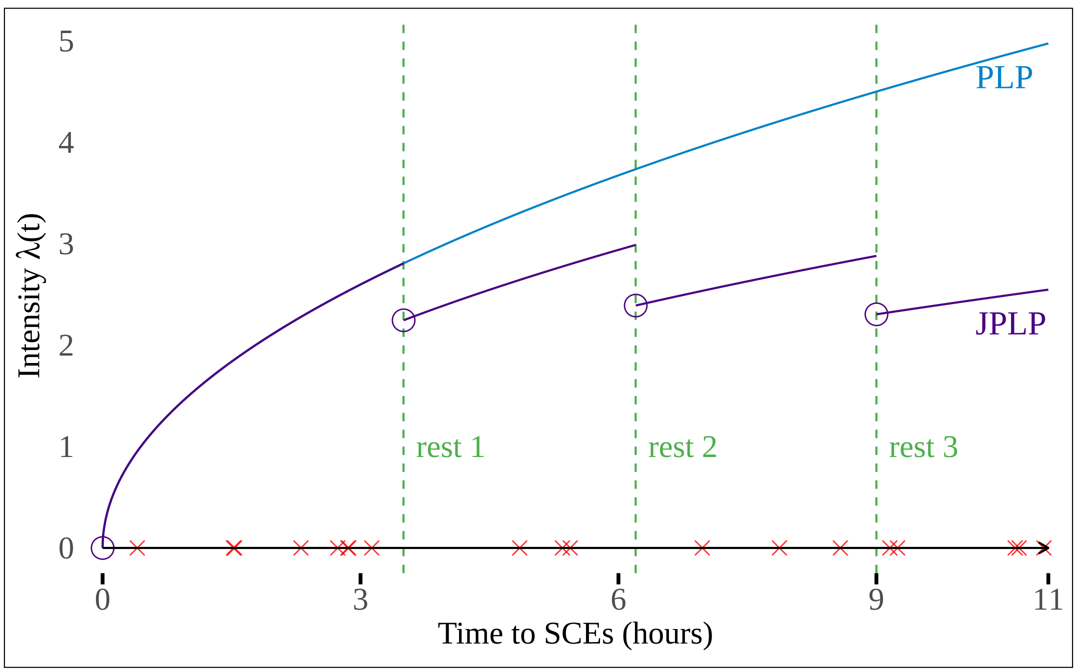

Figure 1: An illustration of a simulated intensity function of PLP and JPLP. The x-axis shows time in hours since start and y-axis shows the intensity of SCEs. The crosses mark the time to SCEs and the vertical dotted lines indicates the time of the rests.

The structure of this article is as follows. In Section II, we define our terminology and notation for shifts, segments, and events for naturalistic driving data generated by commercial truck drivers. In Section III, we specify our proposed PLP and JPLP models, their intensity functions and likelihood functions. In section IV, we present the results of real data analyses for 496 commercial truck drivers using PLP and JPLP. In Section V, simulation studies are conducted to demonstrate the validity of our code and the consequences if the models are not specified correctly. In Section VI, strengths, possible limitations, and future research directions are discussed. To facilitate the replication of our analysis, we provide a simulated data set, description on data structure, and `Stan` and `R` code for Bayesian PLP and JPLP estimation as supplementary material, which we host online on a `GitHub` page.

II. TERMINOLOGY AND NOTATION

Figure 2 presents a time series plot of speed data for a sample truck driver (including two shifts and six segments nested within the shifts) and arrows suggesting shifts and segments. We use $d = 1, 2, \dots, D$ as the index for different drivers. A shift $s = 1, 2, \dots, S_d$ is on-duty periods with no breaks longer than 10 hours for driver d. Per the *hours of service* regulations (Federal Motor Carrier Safety Administration, 2020b), a shift must be no more than 14 hours with no more than 11 hours of driving. This leads to the phenomena that multiple segments $r = 1, 2, \dots, R_{d,s}$ are separated by breaks longer than 30 minutes but less than 10 hours for each driver d and shift s.

SCEs can occur any time in the segments whenever preset kinematic thresholds are triggered while driving. We use $i = 1, 2, \dots, I_{d,s}$ as the index for the i-th SCE for driver d in shift s. For each SCE, $t_{d,s,i}$ is the time to the i-th SCE for driver d measured from the

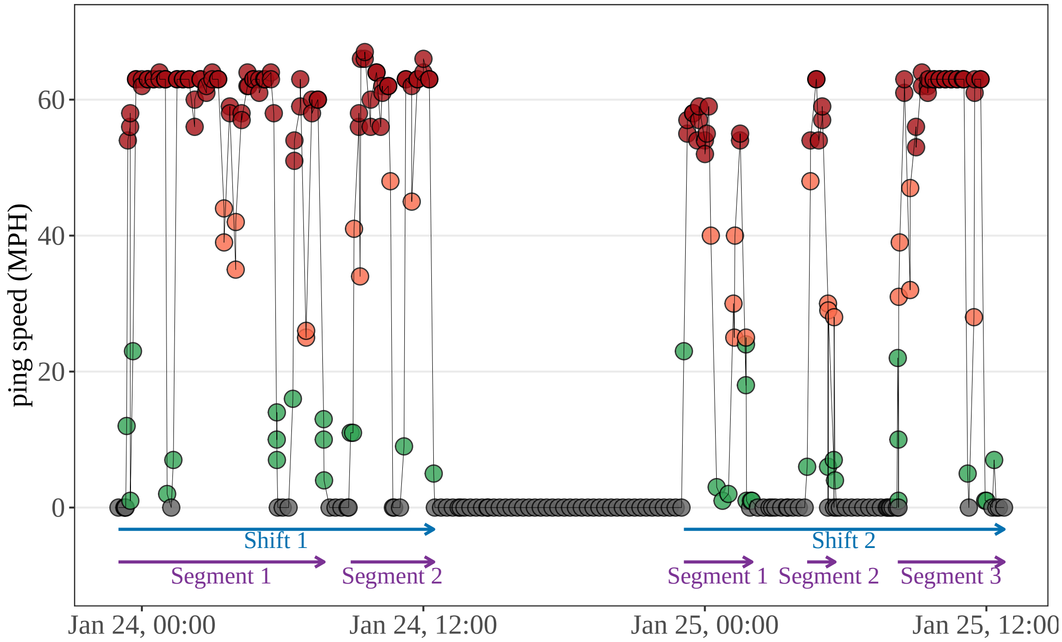

Figure 2: Time series plot of naturalistic truck driving sample ping data (points) and the aggregation process from pings to shifts and segments (arrows).

beginning of the s-shift and the rest times between segments are excluded from calculation. $n_{d,s,r}$ is the number of SCEs for segment r within shift s for driver d. $a_{d,s,r}$ is the end time of segment r within shift s for driver d.

III. MODELS

A. Non-homogeneous Poisson Process (NHPP) and Power Law Process

We assume the times to SCEs t follow a non-homogeneous Poisson process, whose intensity function $\lambda(t)$ is non-constant, having the functional form

$$\lambda_{\text{PLP}}(t) = \frac{\beta}{\theta}\left(\frac{t}{\theta}\right)^{\beta-1}, \tag{1}$$

where the shape parameter β indicates reliability improvement ($\beta < 1$), constant ($\beta = 1$), or deterioration ($\beta > 1$), and the scale parameter θ determines the rate of events. We assume the intensity function of a power law process since it is an established model (Rigdon and

Basu, 1989, 2000) with a flexible functional form and allows for relatively simple inference.

B. Bayesian Hierarchical Power Law Process (PLP)

The Bayesian hierarchical power law process is parameterized as

$$\begin{aligned} t_{d,s,1}, t_{d,s,2}, \cdots, t_{d,s,n_{d,s}} &\sim \text{PLP}(\beta, \theta_{d,s}, \tau_{d,s}) \\ \log \theta_{d,s} &= \gamma_{0d} + \gamma_1 x_{d,s,1} + \gamma_2 x_{d,s,2} + \cdots + \gamma_k x_{d,s,k} \\ \gamma_{01}, \gamma_{02}, \cdots, \gamma_{0D} &\sim \text{i.i.d. } N(\mu_0, \sigma_0^2), \end{aligned} \tag{2}$$

where $t_{d,s,i}$ is the time to the i-th event for driver d in shift s, $\tau_{d,s} = a_{d,s,R_{d,s}}$ is the length of time of shift s (truncation time) for driver d, and $n_{d,s} = \sum_{r=1}^{n_{d,s}}$ is the number of SCEs in shift s for driver d. The priors for the parameters and hyperparameters are taken to be the relatively non-informative distributions

$$\begin{aligned} \beta &\sim \text{Gamma}(1, 1) \\ \gamma_1, \gamma_2, \cdots, \gamma_k &\sim \text{i.i.d. } N(0, 10^2) \\ \mu_0 &\sim N(0, 5^2) \\ \sigma_0 &\sim \text{Gamma}(1, 1). \end{aligned} \tag{3}$$

The likelihood function of event times generated from a PLP for driver d in shift s can be formulated based on Rigdon and Basu (2000, p. 60) as

$$L_{d,s}(\beta, \gamma_{0d}, \gamma | \mathbf{X}_d, \mathbf{W}_s) = \begin{cases} \exp\Big(-(\tau_{d,s}/\theta_{d,s})^{\beta}\Big), & \text{if } n_{d,s} = 0, \\ \Big(\prod_{i=1}^{n_{d,s}} \beta \theta_{d,s}^{-\beta} t_{d,s,i}^{\beta-1}\Big) \exp\Big(-(\tau_{d,s}/\theta_{d,s})^{\beta}\Big), & \text{if } n_{d,s} > 0, \end{cases} \tag{4}$$

where $\mathbf{X}_d$ indicates driver specific variables (e.g. driver age and gender), $\mathbf{W}_s$ represents shift specific variables (e.g. precipitation and traffic), and $\theta_{d,s}$ is the function of parameters $\gamma_{0d}, \gamma_1, \gamma_2, \ldots, \gamma_k$ and variables $x_{d,s,1}, x_{d,s,2}, \ldots, x_{d,s,k}$ given in the third line of Equation (2).

The full likelihood function for all drivers can be computed using:

$$L = \prod_{d=1}^{D} \prod_{s=1}^{S_d} L_{d,s}(\beta, \gamma_{0d}, \gamma | \mathbf{X}_d, \mathbf{W}_s) \tag{5}$$

where $L_{d,s}(\beta, \gamma_{0d}, \gamma | \mathbf{X}_d, \mathbf{W}_s)$ is provided in Equation (4). Models like this are often used in the literature for repairable systems reliability (Rigdon and Basu, 2000). Here, a *failure* can be thought of as the occurrence of a SCE.

C. Bayesian Hierarchical Jump Power Law Process (JPLP)

Since the Bayesian hierarchical PLP does not account for rest breaks ($r = 1, 2, \ldots, R_{d,s}$) within shifts and their associated potential performance improvement, we propose a Bayesian hierarchical JPLP with an additional jump parameter κ. Our proposed JPLP has the following piece-wise intensity function

$$\begin{aligned} &\lambda_{\text{JPLP}}(t|d, s, r, \beta, \gamma_{0d}, \gamma, \mathbf{X}_d, \mathbf{W}_s) = \\ &\qquad \begin{cases} \kappa^0 \lambda(t|\beta, \gamma_{0d}, \gamma, \mathbf{X}_d, \mathbf{W}_s), & 0 < t \leq a_{d,s,1}, \\ \kappa^1 \lambda(t|\beta, \gamma_{0d}, \gamma, \mathbf{X}_d, \mathbf{W}_s), & a_{d,s,1} < t \leq a_{d,s,2}, \\ \vdots & \vdots \\ \kappa^{R-1} \lambda(t|\beta, \gamma_{0d}, \gamma, \mathbf{X}_d, \mathbf{W}_s), & a_{d,s,R-1} < t \leq a_{d,s,R}, \end{cases} \\ &\qquad = \kappa^{r-1} \lambda(t|d, s, r, \kappa, \beta, \gamma_{0d}, \gamma, \mathbf{X}_d, \mathbf{W}_s), \quad a_{d,s,r-1} < t \leq a_{d,s,r}, \end{aligned} \tag{6}$$

where κ is the change in intensity function once a driver takes a break, and $a_{d,s,r}$ is the end time of segment r within shift s for driver d. By definition, the end time of the zero$^{\text{th}}$ segment $a_{d,s,0} = 0$ and the end time of the last segment for driver d within the s^{th} shift equals the shift end time ($a_{d,s,R_{d,s}} = \tau_{d,s}$). We assume that κ is constant across drivers and shifts.

The Bayesian hierarchical JPLP model is parameterized as

$$\begin{aligned} t_{d,s,1}, t_{d,s,2}, \cdots, t_{d,s,n_{d,s}} &\sim \text{JPLP}(\beta, \theta_{d,s}, \tau_{d,s}, \kappa) \\ \log \theta_{d,s} &= \gamma_{0d} + \gamma_1 x_{d,s,1} + \gamma_2 x_{d,s,2} + \cdots + \gamma_k x_{d,s,k} \\ \gamma_{01}, \gamma_{02}, \cdots, \gamma_{0D} &\sim \text{i.i.d. } N(\mu_0, \sigma_0^2). \end{aligned} \tag{7}$$

With the exception of the κ parameter, the above formulation is identical with that presented in Equation (2). We set the prior distribution for κ as uniform(0, 2), which allows the intensity function to change by a factor that ranges from 0 to 2 at rest breaks. The priors and hyperpriors for the JPLP are assigned as

$$\begin{aligned} \beta &\sim \text{Gamma}(1, 1) \\ \kappa &\sim \text{Uniform}(0, 2) \\ \gamma_1, \gamma_2, \cdots, \gamma_k &\sim \text{i.i.d. } N(0, 10^2) \\ \mu_0 &\sim N(0, 5^2) \\ \sigma_0 &\sim \text{Gamma}(1, 1). \end{aligned} \tag{8}$$

The likelihood function of event times generated from a JPLP for driver d on shift s is defined as

$$\begin{aligned} L_{d,s}^*(\kappa, \beta, \gamma_{0d}, \gamma | \mathbf{X}_d, \mathbf{W}_s) &= \Big(\prod_{i=1}^{n_{d,s}} \lambda_{\text{JPLP}}(t_{d,s,i})\Big) \exp(-\int_0^{\tau_{d,s}} \lambda_{\text{JPLP}}(u) du) \\ &\begin{cases} \exp\Big(-\int_0^{\tau_{d,s}} \lambda_{\text{JPLP}}(u) du\Big), & \text{if } n_{d,s} = 0, \\ \Big(\prod_{i=1}^{n_{d,s}} \lambda_{\text{JPLP}}(t_{d,s,i})\Big) \exp\Big(-\int_0^{\tau_{d,s}} \lambda_{\text{JPLP}}(u) du\Big), & \text{if } n_{d,s} > 0, \end{cases} \end{aligned} \tag{9}$$

where the piecewise intensity function $\lambda_{\text{JPLP}}(t_{d,s,i})$ is given in Equation (6). Since the intensity function depends on the segment r for a given driver d on shift s, it is easier to present the likelihood function at a segment level, which can be computed as

$$
\begin{aligned}
&L^*_{d,s,r}(\kappa, \beta, \gamma_{0d}, \gamma | \mathbf{X}_d, \mathbf{W}_r) = \\
&\qquad \begin{cases}
\exp\Big(-\displaystyle\int_{a_{d,s,r-1}}^{a_{d,s,r}} \lambda_{\text{JPLP}}(u)du\Big), & \text{if } n_{d,s,r} = 0, \\
\Big(\displaystyle\prod_{i=1}^{n_{d,s,r}} \lambda_{\text{JPLP}}(t_{d,s,r,i})\Big) \exp\Big(-\displaystyle\int_{a_{d,s,r-1}}^{a_{d,s,r}} \lambda_{\text{JPLP}}(u)du\Big), & \text{if } n_{d,s,r} > 0,
\end{cases}
\end{aligned} \tag{10}
$$

where the intensity function λ_{JPLP} is fixed for driver d on shift s and segment r, $t_{d,s,r,i}$ denotes the time to the i^{th} SCE for driver d on shift s and segment r measured from the beginning of the shift, and $n_{d,s,r}$ is the number of SCEs for driver d on shift s and segment r.

Compared to the PLP likelihood function given in Equation (5) where $\mathbf{W}_s$ are assumed to be fixed numbers during an entire shift, the rewritten likelihood function for JPLP in Equation (10) assumes that the external covariates $\mathbf{W}_r$ vary between different segments in a shift. In this way, the JPLP can account for the variability between different segments within a shift. Therefore, the overall likelihood function for drivers $d = 1, 2, \ldots, D$, their corresponding shifts $s = 1, 2, \ldots, S_d$, and segments $r = 1, 2, \ldots, R_{d,s}$ can be computed as

$$
L^* = \prod_{d=1}^{D} \prod_{s=1}^{S_d} \prod_{r=1}^{R_{d,s}} L^*_{d,s,r}, \tag{11}
$$

where $L^*_{d,s,r}$ is a likelihood function given in Equation (10), in which the intensity function λ_{JPLP} has a fixed functional form provided in the last line of Equation (6) for a certain driver d in a given shift s and segment r.

IV. REAL DATA ANALYSIS

A. Data description

The NDS dataset was generated by an on-board sensor monitoring system based on the routes driven by 496 regional large-truck drivers between April 2015 and March 2016. Note that a regional driver's job typically entails moving freight within a geographic region encompassing several surrounding states. As such, they are typically on the road for five days or more, returning home on a (bi-)weekly basis. A total of 13,187,289 ping records were generated, with a total traveled distance of 20,042,519 miles in 465,641 hours (average speed 43 miles per hour). Each ping records the date and time (year, month, day, hour, minute, and second), latitude and longitude (with precision of five decimal places), driver identification number, and speed at that time point. The geographic distribution of non-zero-speed (active) pings is depicted in Figure 3, which shows that most pings correlate with the U.S.'s population density. These pings were then aggregated into 64,860 shifts and 180,408 segments.

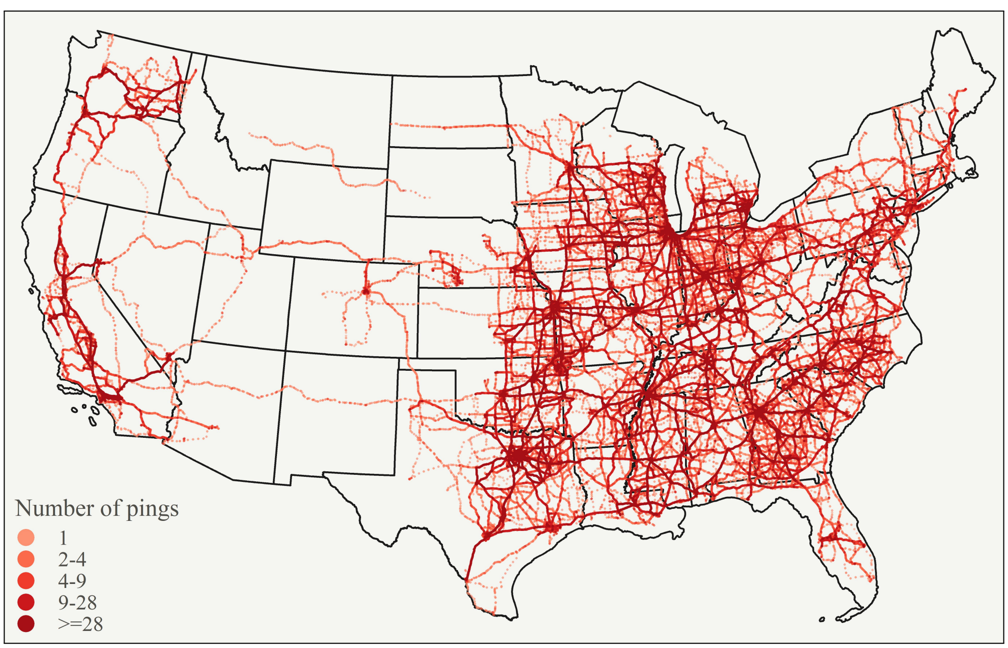

Figure 3: Active pings captured from the 496 regional commercial truck drivers.

Independent of the active, *safe driving*, ping data, 8,386 kinematic SCEs were captured. This corresponds to an overall SCE rate of approximately 0.42 per one thousand miles driven. The observed SCEs were divided into three categories: (a) 3,941 (47%) headway events, where the sensor-based monitoring system captures sustained tailgating for ≥ 118 seconds at an unsafe gap time ≤ 2.8 seconds; (b) 3,576 (42.6%) hard brakes, where the truck decelerates at a rate ≥ 9.5 miles per hour per second; and (c) 869 (10.4%) collision mitigation events, which corresponded to instances when a truck's forward-collision-mitigation system was initiated. Note that headway represents the least severe SCE since no intervention was needed. On the other hand, collision mitigation is the most severe since the truck's system overrides the driver's control by automatically applying the brakes. Furthermore, Cai et al. (2020) established the association between crashes and SCEs while also showing that more severe SCEs had a larger association with crashes.

To complement the datasets provided by the company, we queried historical weather data (precipitation probability, precipitation intensity, and wind speed) using the `DarkSky` Application Programming Interface, which provides hour-by-hour nationwide historic weather conditions for specific latitude-longitude-date-time combinations (The Dark Sky Company, LLC, 2020). The weather data were then merged back to the ping data set and aggregated to shift- and segment-level by taking the mean. Table 1 presents the summary statistics of the driver-, shift-, segment-level variables in our data set.

B. Real data analysis results

We applied the hierarchical Bayesian PLP and JPLP models to this data as specified in Equations (2) and (7). Since we have several types of SCEs, we then applied the JPLP to

Table 1: Summary statistics of driver-, shift-, and segment-level variables

Variable	**Statistics**
Median [IQR] of *driver*-level variables (N = 496)	
Age	47 [36, 55]
Race (N (percent))	
White	246 (49.6%)
Black	206 (41.5%)
Other	44 (8.9%)
Male	460 (92.7%)
Distance	34422.9 [13707.5, 68660.9]
Driving hours	808.1 [337.8, 1626.4]
Mean speed	43.1 [40.8, 44.7]
Mean (S.D.) of *shift*-level variables (N = 64,860)	
Speed S.D.	22.6 (4.3)
Preci. intensity	0.0 (0.0)
Preci. prob.	0.1 (0.2)
Wind speed	3.6 (2.5)
Mean (S.D.) of *segment*-level variables (N = 180,408)	
Speed S.D.	18.6 (7.8)
Preci. intensity	0.0 (0.0)
Preci. prob.	0.1 (0.2)
Wind speed	3.6 (2.9)

Abbreviations:
IQR: interquartile range; S.D.: standard deviation;
Preci. intensity: precipitation intensity;
Precip. prob.: precipitation probability.

the three different types of SCEs separately. Samples of the posterior distributions were drawn using the probabilistic programming language `Stan` in `R` (Carpenter et al., 2017; Stan Development Team, 2018). The convergence of the Hamiltonian Monte Carlo was checked using the Gelman-Rubin diagnostic statistics $\hat{R}$ (Gelman et al., 1992), effective sample size (ESS), and trace plots.

Table 2 presents the posterior mean, 95% credible interval (CI), Gelman-Rubin diagnostic statistics $\hat{R}$, and ESS for the sample 496 regional drivers using PLP and JPLP. In both the PLP and JPLP models, the posterior means of the shape parameters β are less than one and the 95% credible intervals exclude one, indicating SCEs occur in the early stages of the shifts. In the JPLP, the reliability jump parameter κ was close to 1, suggesting that within a shift, rests have very minor effects on the intensity of SCEs.

Table 2: Posterior mean, 95% credible interval, Rhat, and effective sample size (ESS) of PLP and JPLP models for 496 commercial truck drivers

Parameters	Power law process				Jump power law process			
	mean	95% CI	$\hat{R}$	ESS	mean	95% CI	$\hat{R}$	ESS
$\hat{\beta}$	0.968	(0.948, 0.988)	1.000	6,500	0.962	(0.940, 0.985)	1.001	3,798
$\hat{\kappa}$					1.020	(0.995, 1.045)	1.000	5,400
$\hat{\mu}_0$	3.038	(2.397, 3.688)	1.001	2,979	3.490	(2.899, 4.091)	1.001	3,079
$\hat{\sigma}_0$	0.974	(0.897, 1.058)	1.000	9,581	0.982	(0.905, 1.066)	1.000	9,050
Age	0.003	(-0.005, 0.012)	1.001	2,250	0.004	(-0.005, 0.012)	1.001	2,566
Race: black	-0.113	(-0.329, 0.103)	1.002	1,951	-0.130	(-0.342, 0.087)	1.001	2,277
Race: other	-0.343	(-0.707, 0.021)	1.001	2,833	-0.361	(-0.729, 0.010)	1.001	3,334
Gender: female	-0.071	(-0.441, 0.300)	1.001	3,069	-0.071	(-0.435, 0.296)	1.001	4,162
Mean speed	0.019	(0.016, 0.023)	1.000	20,229	0.015	(0.013, 0.018)	1.000	19,827
Speed variation	0.026	(0.017, 0.034)	1.000	24,825	0.017	(0.013, 0.022)	1.000	13,127
Preci. intensity	-3.608	(-6.181, -0.935)	1.000	22,025	-2.136	(-3.785, -0.368)	1.000	24,397
Preci. prob.	0.397	(0.168, 0.628)	1.000	21,416	0.121	(-0.050, 0.296)	1.000	25,329
Wind speed	0.018	(0.008, 0.029)	1.000	32,980	0.010	(0.001, 0.018)	1.000	33,093

Abbreviations:

95% CI: 95% credible interval; ESS: effective sample size;

PLP: power law process; JPLP: jump power law process;

Preci. intensity: precipitation intensity; Precip. prob.: precipitation probability.

In Figure 4, we present the histograms for estimates of the random intercepts. The visualization indicates that there is considerable variability across drivers. The random intercepts γ_{0d} are on average larger in the JPLP model than those in the PLP model, while variability of random intercepts is similar in the two models. These patterns are consistent with the parameter estimates of μ_0 and σ_0 in Table 2.

In terms of the convergence of the Hamiltonian Monte Carlo, all the Gelman-Rubin diagnostic statistics $\hat{R}$ are less than 1.1 and the ESSs are greater than 1,000. Furthermore, the trace plots of important variables $(\beta, \kappa, \mu_0, \sigma_0)$, presented in Figure 5, indicate that all

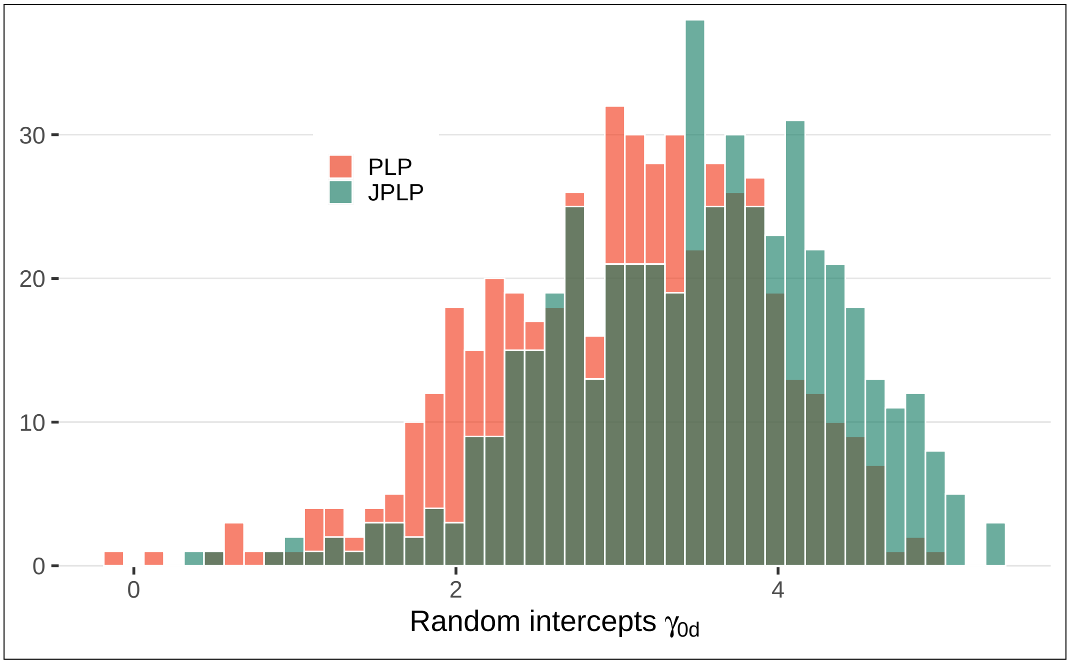

Figure 4: Histogram of random intercepts γ_{0d} across the 496 drivers.

four chains for the parameters are well mixed. Thus, the evidence suggests that a steady state posterior distribution have been reached for both the PLP and JPLP models.

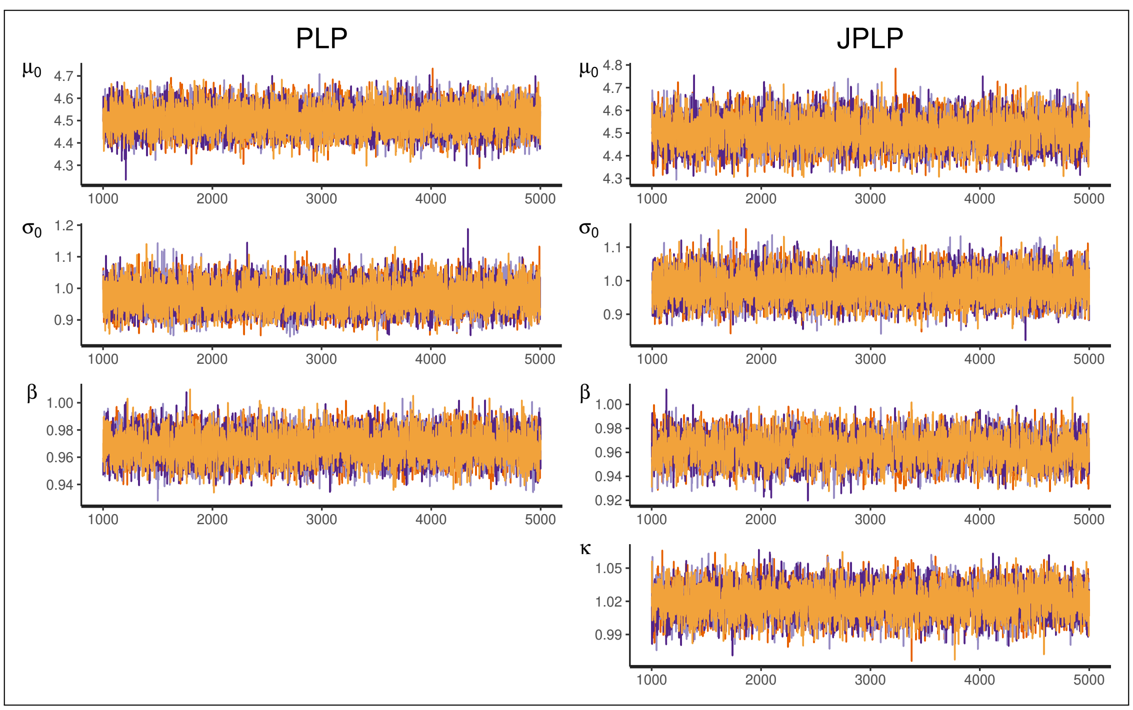

Figure 5: Trace plots of select parameters in PLP (left column) and JPLP (right column) for all types of SCEs

In an attempt to estimate the account of rest breaks on the three different SCEs, we estimated the JPLP models for each SCE and the results are presented in Table 3. Headway and hard brakes are similar: the posterior means and 95% credible intervals for parameters β and κ are nearly identical, although the hyperparameters for random intercepts are quite different. The $\hat{\beta} < 1$ and $\hat{\kappa} > 1$ suggest that headway and hard brake tend to occur in the early stages of driving shifts, and taking short breaks will slightly increase the intensity of these two events (although the credible intervals contain 1). In contrast, collision mitigation shows a different pattern: it tends to occur in later stages of driving shifts, and taking short breaks will reduce the intensity of the event. The variability estimate of random intercepts across drivers (σ_0) is stronger for headway than hard brake, and collision mitigation.

Table 3: Parameter estimates and 95% credible intervals for jump power law process on 496 truck drivers, stratified by different types of safety-critical events

Parameters	**Headway**	**Hard brake**	**Collision mitigation**
$\hat{\beta}$	0.989 (0.956, 1.023)	0.922 (0.889, 0.955)	1.020 (0.950, 1.096)
$\hat{\kappa}$	1.034 (0.998, 1.071)	1.034 (0.996, 1.072)	0.890 (0.821, 0.964)
$\hat{\mu_0}$	7.096 (6.083, 8.139)	3.470 (2.770, 4.199)	4.729 (3.836, 5.666)
$\hat{\sigma_0}$	1.564 (1.411, 1.730)	1.073 (0.973, 1.182)	0.922 (0.786, 1.074)
Age	-0.006 (-0.020, 0.009)	0.011 (0.001, 0.021)	0.002 (-0.009, 0.012)
Race: black	0.184 (-0.170, 0.546)	-0.312 (-0.565, -0.064)	0.113 (-0.153, 0.386)
Race: other	0.306 (-0.340, 0.967)	-0.539 (-0.968, -0.106)	0.100 (-0.373, 0.605)
Gender: female	0.266 (-0.343, 0.870)	-0.217 (-0.654, 0.230)	-0.181 (-0.675, 0.309)
Mean speed	-0.026 (-0.031, -0.021)	0.043 (0.039, 0.047)	0.039 (0.032, 0.046)
Speed variation	-0.009 (-0.017, -0.002)	0.017 (0.010, 0.024)	0.013 (-0.002, 0.027)
Preci. intensity	-0.771 (-4.306, 3.188)	-1.912 (-3.924, 0.269)	-0.676 (-6.329, 6.297)
Preci. prob.	0.694 (0.376, 1.015)	-0.495 (-0.724, -0.263)	0.808 (0.206, 1.423)
Wind speed	0.003 (-0.009, 0.015)	0.019 (0.005, 0.034)	0.000 (-0.025, 0.026)

Abbreviations:

Preci. intensity: precipitation intensity; Precip. prob.: precipitation probability.

V. SIMULATION STUDY

A. Simulation setting

We conducted a simulation study to evaluate the performance of our proposed NHPP and JPLP under different simulation scenarios. We performed 1,000 simulations to each of the following three scenarios with different number of drivers $D = 10, 25, 50, 75, 100$:

1. Data generated from a PLP and estimated assuming a PLP (PLP),
2. Data generated from a JPLP and estimated assuming a JPLP (JPLP),
3. Data generated from a JPLP, but estimated assuming a PLP (PLP $\leftarrow$ JPLP).

Specifically, for each driver, the number of shifts is simulated from a Poisson distribution with the mean parameter of 10. We assume there are three predictor variables x_1, x_2, x_3 for θ ($k = 3$, and the predictors are simulated from: $x_1 \sim \text{Normal}(1, 1^2)$, $x_2 \sim \text{Gamma}(1, 1)$, and $x_3 \sim \text{Poisson}(2)$. The shift time $\tau_{d,s}$ is generated from $\tau_{d,s} \sim \text{Normal}(10, 1.3^2)$ to emulate the real data shift time distribution.

The parameters and hyperparameters are assigned the following values or generated from the following process:

$$
\begin{aligned}
&\mu_0 = 0.2,\ \sigma_0 = 0.5, \\
&\gamma_{01}, \gamma_{02}, \cdots, \gamma_{0D} \sim \text{i.i.d. } N(\mu_0, \sigma_0^2) \\
&\gamma_1 = 1,\ \gamma_2 = 0.3,\ \gamma_3 = 0.2 \\
&\theta_{d,s} = \exp(\gamma_{0d} + \gamma_1 x_1 + \gamma_2 x_2 + \gamma_3 x_3) \\
&\beta = 1.2,\ \kappa = 0.8.
\end{aligned}
\tag{12}
$$

After the predictor variables, shift time, and parameters are generated, the time to events are generated from either the PLP or the JPLP.

The parameters are then estimated using the likelihood functions given in Equations (5) and (11) using the probabilistic programming language `Stan` in R (Carpenter et al., 2017; Stan Development Team, 2018), which uses efficient Hamiltonian Monte Carlo to sample from the posterior distributions. For each simulation, one chain is applied, with 2,000 warmup and 2,000 post-warmup iterations drawn from the posterior distributions.

B. Simulation results

The simulation results are shown in Table 4. For the five sets of drivers $D = 10, 25, 50, 75, 100$ in each of the three scenarios, mean of estimation bias $\Delta = \hat{\mu} - \mu$, and mean of standard error estimates for parameters $\beta, \kappa, \gamma_1, \gamma_2, \gamma_3$ and hyperparameters μ_0 and σ are calculated.

When the models were specified correctly, the bias seems converge to 0 as the number of drivers increases; the standard errors converge to 0 roughly proportional to the square root of the number of drivers ($\sqrt{D}$), which is consistent with the central limit theorem. When the models are not specified correctly, there are still a fair amount of bias when the number of drivers increases and the speed of converging to zero is not consistent with either the other two correctly specified simulation scenarios or the central limit theorem. The Gelman-Rubin diagnostic $\hat{R}$ were all lower than 1.1 and no low effective sample size (ESS) issues were reported in `Stan`, suggesting that steady posterior distributions were reached while estimating the parameters of the simulated data sets.

Table 4: Biases Δ and standard errors (S.E.) for PLP, JPLP, and PLP ← JPLP simulation results

Scenario	D	estimate	β	κ	μ_0	σ_0	γ_1	γ_2	γ_3
PLP	10	bias Δ	-0.0102		-0.0282	0.0527	0.0203	0.0095	0.0067
PLP	25	bias Δ	-0.0045		-0.0015	0.0220	0.0066	0.0046	0.0012
PLP	50	bias Δ	-0.0017		-0.0068	0.0077	0.0040	0.0033	0.0005
PLP	75	bias Δ	-0.0017		-0.0026	0.0091	0.0034	0.0004	0.0007
PLP	100	bias Δ	-0.0006		-0.0034	0.0042	0.0009	0.0009	0.0003
PLP	10	S.E.	0.0589		0.2401	0.1722	0.0777	0.0696	0.0413
PLP	25	S.E.	0.0360		0.1392	0.0916	0.0459	0.0414	0.0247
PLP	50	S.E.	0.0254		0.0960	0.0610	0.0316	0.0286	0.0172
PLP	75	S.E.	0.0207		0.0784	0.0497	0.0258	0.0232	0.0139
PLP	100	S.E.	0.0179		0.0667	0.0420	0.0220	0.0198	0.0119
JPLP	10	bias Δ	-0.0226	0.0149	-0.0401	0.0696	0.0331	0.0218	0.0092
JPLP	25	bias Δ	-0.0131	0.0084	-0.0202	0.0219	0.0158	0.0081	0.0039
JPLP	50	bias Δ	-0.0057	0.0032	0.0014	0.0111	0.0037	0.0012	0.0039
JPLP	75	bias Δ	-0.0058	0.0028	0.0057	0.0097	0.0060	0.0012	0.0006
JPLP	100	bias Δ	-0.0043	0.0023	-0.0004	0.0041	0.0048	0.0003	0.0008
JPLP	10	S.E.	0.0828	0.0573	0.2556	0.1854	0.0992	0.0834	0.0498
JPLP	25	S.E.	0.0512	0.0360	0.1453	0.0960	0.0586	0.0477	0.0288
JPLP	50	S.E.	0.0366	0.0256	0.0999	0.0647	0.0406	0.0334	0.0201
JPLP	75	S.E.	0.0298	0.0208	0.0812	0.0519	0.0331	0.0272	0.0164
JPLP	100	S.E.	0.0258	0.0179	0.0699	0.0442	0.0287	0.0233	0.0141
PLP ← JPLP	10	bias Δ	-0.1843		-0.1234	0.1599	0.1923	0.0645	0.0434
PLP ← JPLP	25	bias Δ	-0.1740		-0.0866	0.1053	0.1769	0.0514	0.0374
PLP ← JPLP	50	bias Δ	-0.1734		-0.0854	0.0977	0.1718	0.0531	0.0355
PLP ← JPLP	75	bias Δ	-0.1724		-0.0874	0.0960	0.1686	0.0511	0.0346
PLP ← JPLP	100	bias Δ	-0.1713		-0.0811	0.0925	0.1674	0.0512	0.0349
PLP ← JPLP	10	S.E.	0.0580		0.2952	0.2078	0.1041	0.0946	0.0559
PLP ← JPLP	25	S.E.	0.0354		0.1671	0.1095	0.0609	0.0546	0.0329
PLP ← JPLP	50	S.E.	0.0250		0.1167	0.0743	0.0423	0.0383	0.0230
PLP ← JPLP	75	S.E.	0.0204		0.0946	0.0601	0.0344	0.0310	0.0186
PLP ← JPLP	100	S.E.	0.0177		0.0810	0.0514	0.0297	0.0266	0.0160

VI. DISCUSSION

In this article, we proposed a Bayesian hierarchical NHPP with PLP intensity function and a Bayesian hierarchical JPLP to model naturalistic truck driving data. Our motivation comes from more popular use of naturalistic driving data sets in the recent decade and real-life truck driving characteristics of multiple segments nested within shifts. The proposed JPLP accounts for the characteristics of multiple rests within a shift among commercial truck drivers. Simulation studies showed the consistency of the Bayesian hierarchical estimation if the models are specified correctly, as well as the persistent bias when the models are not specified correctly. A case study of 496 commercial truck drivers demonstrates a considerable amount of variability exist across drivers. Headway and hard brake tend to occur in early stages while collision mitigation and rolling stability tend to occur in later stages.

The models we have studied are based on models that have been widely applied to the reliability of repairable systems. The NHPP is a model that implies a minimal repair is done at each failure; that is, the reliability of the system is restored to its condition immediately before the failure. For the case of repairable systems, the time required for repair is usually not included in the cumulative operating time. In our case, the NHPP implies that the occurrence of an SCE does not change the intensity of the process. There is no repair time to account for because the driver continues to drive immediately after the SCE. A rest break for drivers is analogous to a preventive maintenance for a repairable system whereby a system's reliability is (possibly) improved by performing the maintenance. Our JPLP model here is similar to the modulated power law process ((Lakey and Rigdon, 1993; Black and Rigdon, 1996)), except their model assumed that the reliability might be improved at every failure/repair.

Our models differ in several respects from the repairable systems models. Our models involve the use of covariates, such as weather conditions and driver demographics. In addition, the heterogeneity of drivers required a hierarchical model. In fact, one important finding is that driver-to-driver variability accounts for much of the variability of SCEs. Finally, the size of the data (496 drivers, with over 13 million pings) is much larger than would normally be encountered in a reliability setting.

From the JASA papers I read, the last paragraph(s) are limitations/future work. So I would vote for keeping. Our work can be extended in several aspects in the future. First, the assumption of proportion reliability jump may not hold. Other proper assumptions include reliability jumping for a fixed-amount jump or jumping dependent on the length of the rest. Additionally, in our proposed JPLP, the length of breaks within shifts are ignored to simply the parameterization and likelihood function. In truck transportation practice, longer breaks certainly have larger effects on reliability jump, hence the relationship between reliability jump and the length of breaks can have more complex functional forms, so it would be of interest to test different forms of reliability change as a function of the length of break.

SUPPLEMENTARY MATERIALS

Due to the non-disclosure agreement (NDA), we cannot make the driving dataset publicly accessible. Therefore, we provide instead a simulated dataset that is similar to the real data, which allows us to mask any company sensitive data, yet allow for the replication of our work by industry and academic researchers. Note that we limited the simulated dataset to a smaller number of drivers to ensure that the computations can be completed in a reasonable amount of time, without the need for high performance computing resources. The online supplementary materials contain the `R` code used to simulate PLP and JPLP data, explanations on the data structure as well as `Stan` and `R` code for Bayesian hierarchical PLP and JPLP estimation. The material is organized using an R Markdown document, which is hosted on the following GitHub page https://for-blind-external-review.github.io/JPLP/. The markdown and supplementary material will be moved to a permanent location after the completion of the peer-review process.

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To ensure the anonymity of the author(s), we removed the agencies funding our work. This information would be provided after the peer-review process is completed.

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