

2025-03-06

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*IEEE transactions on intelligent transportation systems (Print)*, (2022), 23(5), pp. 4758-4766.

Publisher: Institute of Electrical and Electronics Engineers

<https://doi.org/10.1109/TITS.2021.3102519>

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# Real-time Adaptation of Driving Time and Rest Periods in Automated Long-Haul Trucking: Development of a system based on biomathematical modelling, fatigue and relaxation monitoring

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**Abstract**— Hours of service regulations govern the working hours of commercial motor vehicle drivers, but these regulations may become more flexible as highly automated vehicles have the potential to afford periods of in-cab rest or even sleep while the vehicle is moving. A prerequisite is robust continuous monitoring of when the driver is resting (to account for reduced time on task) or sleeping (to account for the reduced physiological drive to sleep). The overall aims of this paper are to raise a discussion of whether it is possible to obtain successful rest during automated driving, and to present initial work on a hypothetical data driven algorithm aimed to estimate if it is possible to gain driving time after resting under fully automated driving. The presented algorithm consists of four central components, a heart rate-based relaxation detection algorithm, a camera-based sleep detection algorithm, a fatigue modelling component taking time awake, time of day and time on task into account, and a component that estimates gained driving time. Real-time assessment of driver fitness is complicated, especially when it comes to the recuperative value of in-cab sleep and rest, as it depends on sleep quality, time of day, homeostatic sleep pressure and on the activities that are carried out while resting. The monotony that characterizes for long-haul truck driving is clearly interrupted for a while, but the long-term consequences of extended driving times, including user acceptance of the key stakeholders, requires further research.

**Index Terms**— hours of service regulations, fatigue modelling, relaxation detection, sleep detection, vehicle automation, truck

## I. INTRODUCTION

THE hour of service regulations for professional drivers provides rules for maximum daily and weekly driving times, as well as daily and weekly minimum rest periods. As an example, in the European Union (regulation 561/2006),

the daily driving period shall not exceed 9 hours, the weekly driving time shall not exceed 56 hours, and breaks of at least 45 minutes (separable into 15 minutes followed by 30 minutes) should be taken after 4.5h at the latest, etc. With vehicle automation, these rules may be about to change and a more flexible, risk management-based approach [1] could be more feasible. For example, under automated driving on the equivalence of at least SAE level 4, it may be possible to obtain rest or even sleep while the vehicle is moving. If recuperative rest can be obtained while on the move, it may eventually be possible to extend the maximum daily driving period without causing worse working conditions or increased crash risk. This obviously requires that the operational design domain of the automated system allows the driver to disengage for a sufficiently long period of time.

Real-time adaptation of the allowed driving times would require a system that continuously monitor the drivers' fitness level and estimates how much the driving time should be extended or shortened. In this paper, we outline a first version of such a system. The feasibility of the approach is based on previous research on the recuperative value of brief sleep episodes and rest breaks. According to the theory of sleep/wake regulation, sleep reduces sleepiness in a dose-response manner and even a brief sleep episode (napping) of only 10-20 minutes can improve alertness and sustained attention for the subsequent 1–3 hours as long the individual is not suffering from sleep deprivation [2-4]. Longer naps of 60–90 minutes have stronger beneficial effects, and fatigue may be reduced for up to 8 hours [4]. Homeostatic sleep pressure, sleep quality and circadian regulation has a strong impact on fatigue and is likely to modify the effect of a nap. For example, a nap before the circadian low (late night hours) might be less beneficial in terms

This work was supported by the ADAS&ME project, which is funded by the European Union's Horizon 2020 research and innovation programme under grant agreement No. 688900.

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of more difficulties waking up from sleep than a nap taken earlier in the night. It is also unclear if brief naps shorter than 10 minutes can reduce fatigue and improve performance, even though one advantage with very short sleep episodes is the lack of sleep inertia [5]. Sleep inertia refers to a state characterized by feelings of grogginess and impaired wakefulness that occurs immediately after waking-up from sleep. This side effect is normally stronger for longer sleep episodes and during night-time, close to the circadian low [5]. Thus, a 1 to 1.5-hour nap may cause severely impaired performance during the first 5 to 10 minutes after sleep [6, 7].

Very little research is available on the effect of sleep during automated driving, and no results on the recuperative value of a sleep episode have been reported. Wörle, et al. [8] did however find that the sleep quality obtained while on the move (in a moving-base driving simulator) was low, with subjects waking up quite often, and with only 3 out of 21 sleep-deprived participants reaching deep sleep. Hirsch, et al. [9] found that short (15–20 minutes of sleep) naps may potentially be used as a countermeasure to sleepiness in Level 4 automation if a take-over time between one and seven minutes is granted to counter sleep inertia.

The beneficial effect of rest breaks (time off task not including sleep) on reduced fatigue and improved performance is assumed to be weaker compared to brief sleep periods. Previous research suggests that a short (10–20 minutes) rest break may temporarily improve performance for a period of about 15–20 minutes [10]. It is also likely that a rest break is less effective if the driver is sleep deprived [11]. However, regular breaks have been linked to decreased accident risk in industrial workers and it is likely that breaks reduce time on task related fatigue [11, 12]. Regular rest breaks have also been found to lower the crash risk for truck drivers [13]. It is not clear how the optimal rest break pattern should be organized. One assumption is that longer rest breaks are more beneficial for performance than brief rest breaks, even though repeated, brief, rest breaks may be equally effective as fewer but longer rest breaks [14].

It is important to note that the type of rest that is needed depends on the type of fatigue that the driver experiences [15]. If the driver is suffering from high levels of fatigue caused by overload, which often occurs in parallel to stress, then adequate rest refers to cease driving and temporarily shut off sustained attention demands [16]. In comparison, if fatigue is due to under-stimulation or boredom, then activation rather than rest is required to reduce the level of fatigue. Finally, if fatigue is due to sleep deprivation or night-time driving, then sleep rather than relaxation and inactivity is needed to recuperate the driver [17].

In this paper, we outline a first version of a system that continuously monitor the drivers' fitness level and estimates how much the driving time should be extended or shortened. Fig. 1 provides an overview of the system, with the relaxation detection component that measures rest breaks, the sleep detection component that measures sleep episodes, a fatigue model component that makes use of this information to estimate the current and future fatigue level, and a fourth component that estimates how much driving time that has been gained by resting or sleeping. The aim of this paper is to describe the implementation and development of these four components. The novelty lies in the presented application and in the full system rather than in the individual components.

Although the full system has been implemented and demonstrated in a truck within the ADAS&ME project [18], an empirical evaluation of the system is out of scope of the present paper.

## II. ALGORITHMIC APPROACH

An overview of the algorithmic approach is provided in Fig. 1. The output of the system is a continuous measure that is updated in real-time based on data from the previous five minutes, representing how much extra driving time that the driver has gained by relaxing or sleeping while the truck has been driving in an automated mode. The relaxation detection component was developed based on an existing dataset with 100 car drivers, the sleep detection component was essentially

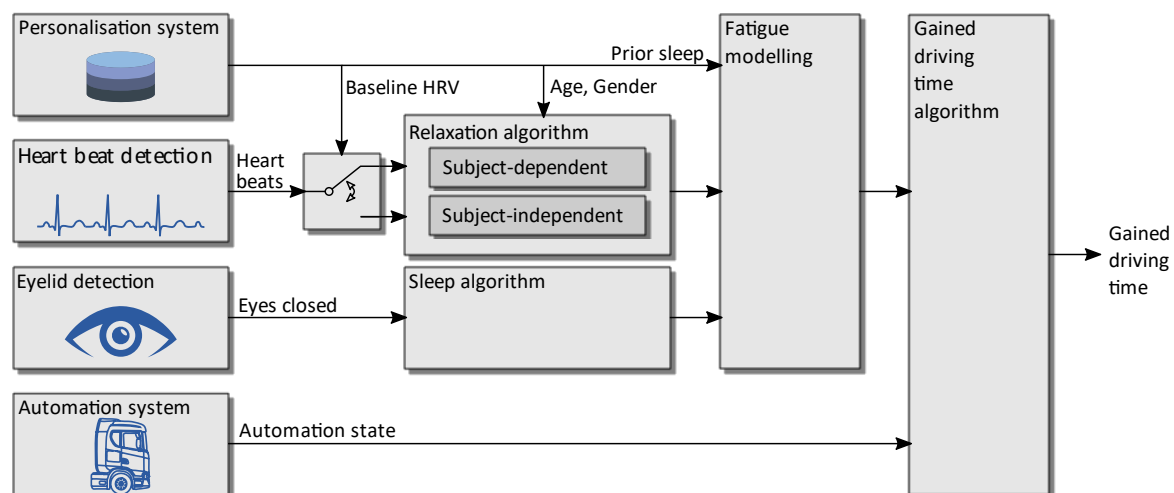


Fig. 1. Flowchart describing the main components of the suggested system to estimate potentially gained driving time while driving in an automated mode.

taken off-the-shelf from a commercial eye tracking provider, and the fatigue modelling and driving time components, respectively, were designed based on literature. A more detailed account of each component is provided in the following sections.

#### A. Relaxation detection algorithm

For practical reasons, the relaxation detection algorithm was developed based on an existing dataset consisting of 100 car drivers. Heart rate and heart rate variability (HRV) metrics were used as features to classify manual driving from relaxation behind the wheel in a stationary vehicle. Disadvantages with this dataset is that it was recorded in a car and not in a truck, and that relaxation data were recorded while standing still. A major advantage is that the gender distribution is equal, something that would have been difficult to achieve in a truck driver population.

1) *Dataset*: The 100 car drivers were evenly distributed in the age groups 20-29, 30-39, 40-49, 50-59 and >60 years, and half of the driver group was women. The participants were not manipulated in any way and were told to drive as they normally do. The experiment took place in the outskirts of Linköping, Sweden, and consisted of 40 minutes of driving on suburban roads, trunk roads and an inter-urban motorway. The driving episodes occurred during daytime between 09.00 and 16.30. Before and after the drives, the participants were instructed to relax with open eyes for 5 minutes while remaining in the car (XC90, Volvo Cars Corporation, Gothenburg, Sweden). The data collection was approved by the regional ethics committee in Linköping, Sweden (EPN Dnr 2017/508-31), and was performed between July 6th and September 26th, 2018.

2) *Pre-processing*: An electrocardiogram (ECG, lead II, NeXus-10 MKII, Mind Media, Herten, Netherlands) was recorded during the experiment. Heart beats were extracted from the ECG by extracting the R-peaks as described by Afonso, et al. [19]. The time difference between successive heart beats (RR-intervals) were converted to normal to normal (NN)-intervals according to Karlsson, et al. [20]. The NN time series were then divided into 5-min segments, matching the pre- and post-drive relaxation events and splitting each drive into about 8 segments. Five minutes is the recommended minimum duration for short-term HRV analysis [21].

Ten standard heart rate variability (HRV) metrics were extracted from each segment: mean NN-interval (mean NN), standard deviation of NN-interval (SD NN), root mean square of successive differences (RMSSD), Poincaré plot standard deviation along the line of identity (SD2), absolute power of the low-frequency band (LF), relative power of the low-frequency band (LF norm), absolute power of the high-frequency band (HF), relative power of the high-frequency band (HF norm), ratio of LF-to-HF power (LF/HF) and sample entropy (SampEn). The low-frequency band was defined as 0.04–0.15 Hz and the high-frequency power was defined as 0.15–0.4 Hz. See Shaffer and Ginsberg [21] for more details about the different HRV metrics.

3) *Statistical analysis*: A series of mixed model analyses of variance (ANOVA) were conducted to verify the effect of the experimental design (reduced heart rate and increased HRV

during relaxation). The 10 HRV metrics were used as dependent variables and condition (drive vs. post-drive relaxation), gender (male vs. female) and age (20–29, 30–39, 40–49, 50–59 and 60+ years) were used as independent variables. Participant was used as a random factor. The significance level was set to 0.05 and Bonferroni corrections was used to account for multiple comparisons.

4) *Machine learning procedure*: A machine learning pipeline was set up with a feature selection step, a classification step and an evaluation step. The dataset was split up into a development set (70%) and a test set (30%), where the development set was used for feature selection and classifier design, while the test set was used for evaluation purposes only. This procedure was repeated 100 times to obtain an estimate of the generalizability of the classifier. A binary classification approach with the two target classes drive versus post-drive relaxation was used. Two separate algorithms were developed, one using subject-dependent HRV features (where the pre-drive baseline HRV values were subtracted from the relaxation and drive HRV values) and one using the subject-independent feature set where this normalisation was not carried out. The former approach will result in better performance since it accounts for individual differences, whereas the latter has the advantage that it works out of the box on unseen drivers.

Feature selection was carried out using Sequential Forward Floating Selection (SFFS) [22]. SFFS was wrapped with a decision tree classifier, using 5-fold cross-validation, 10 cross validation runs and a trade-off between SEN/SPE as optimization score. Since SFFS is known to result in low-dimensional non-redundant feature sets that may be sensitive to noisy data, the SFFS procedure was run repeatedly on different partitions of the development set. The features that were selected in at least 25% of the repetitions were used as the final feature set. Note that age and gender were added amongst the features since they are known to affect HRV [23].

The resulting feature subset was used to classify the data into relaxation or drive using a Gaussian support vector machine (SVM) classifier. The features were standardized, the box constraint level was set to 1 and the kernel scale was set to 2.6. A cost function was used to avoid false negatives (misclassifications of drive as rest). Otherwise, the standard settings from the MATLAB Statistics and Machine Learning Toolbox version 11.7 were used (The Mathworks, Natick, MA, USA).

The relaxation algorithm operates on HRV data calculated every 10 seconds in a 5-minute sliding window. This provides a lower limit to the shortest possible rest episode, which can in theory be 10 seconds long, but that is almost always considerably longer in practise. The output of the algorithm is binary (relaxation versus driving).

#### B. Sleep detection algorithm

In the present version of the suggested system, sleep is estimated via closed eyes. Eyes closed detection is provided by a camera-based eye tracking system (Smart Eye Embedded, Smart Eye AB, Gothenburg, Sweden). Eye closures longer than 60 seconds are here considered as sleep. The output of the sleep detection algorithm is binary (sleep versus awake).

### C. Fatigue modelling

A key component of the envisioned over-all system is a biomathematical fatigue model that makes use of the output from the relaxation and sleep detection algorithms, in combination with homeostatic sleep pressure, to predict the current and future fatigue level of the driver. Homeostatic sleep pressure is here obtained from bed and rise times stored in the personalisation system (Fig. 1).

The implemented model is based on the sleep/wake predictor by Åkerstedt, et al. [24]. The sleep/wake predictor model was also complemented with a time on task and task demand component [25]. The sleep/wake predictor model has previously been validated against objective indicators, such as performance, physiological measures, as well as motor-vehicle crash risk [24].

The sleep/wake predictor estimates the fatigue level based on models of sleep/wake homeostasis and the circadian rhythm. The homeostatic process  $S(t)$  is defined in equation (1), where  $S(t)$  is constrained by a higher ( $a_h = 14.3$ ) and lower ( $a_l = 2.4$ ) asymptote. When awake,  $S(t)$  takes the level of  $S$  at the time of awaking,  $S(t_a)$ , as input, and calculates the increase in fatigue ( $d = 0.0353$ ) as a function of time awake ( $t-t_a$ ). During sleep, there are two different equations describing the homeostatic process. The first describes the part of sleep with high homeostatic pressure before a so-called break time  $t_b$  and the latter equation describes the last part of sleep with lower pressure after  $t_b$ , equation (2). These functions take another parameter  $g \approx -0.38$  to calculate the recovery of alertness as a function of time asleep ( $t-t_s$ ).

$$S(t) = \begin{cases} a_l + (S(t_a) - a_l)e^{-d(t-t_a)} & \text{if awake} \\ S(t_s) + g(t - t_s)(S_b - a_h) & \text{asleep and } t \leq t_b \text{ (1)} \\ a_h - (a_h - S_b)e^{g(t-t_s-t_b)} & \text{asleep and } t > t_b \end{cases}$$

$$t_b = t_s + \frac{S_b - S(t_s)}{g(S_b - a_h)} \quad (2)$$

The circadian and ultradian components  $C(t)$  and  $U(t)$  are related to time of day, equations (3) and (4). Process  $C(t)$  has a period of 24h with a default circadian phase ( $p_c = 18$ ), amplitude ( $a_c = 2.5$ ) and mesor ( $m_c = 0$ ). Process  $U(t)$  has a period of 12h with a default circadian phase ( $p_u = 21$ ), amplitude ( $a_u = 0.5$ ) and mesor ( $m_u = -0.5$ ).

$$C(t) = a_c \cos\left(\frac{2\pi(t-p_c)}{24}\right) \quad (3)$$

$$U(t) = m_u + a_u \cos\left(\frac{2\pi(t-p_u)}{12}\right) \quad (4)$$

The sleep inertia function  $W(t)$  initially increase the fatigue level at the time of waking up with 5% of processes  $S(t_a) + C(t_a) + U(t_a)$  times an exponential recovery ( $W_d = -1.51$ ), equation (5).

$$W(t) = 0.05(S(t_a) + C(t_a) + U(t_a))e^{W_d(t-t_a)} \quad (5)$$

Task demand and time on task,  $R(t)$ , is defined in equation

(6).  $R(t)$  deplete during work periods and recover during rest breaks. The depletion rate is amplified by task demand ( $L = 1$  here, but potentially adapted to current traffic conditions) and sleep pressure ( $S(t) + C(t) + U(t)$ ). While driving, the depletion rate is defined as  $R_d = 1.14$  and while resting, the recovery rate is  $R_r = 11$  according to Peng, et al. [25]. The normalization factor  $R_c = 0.27$  limits the task demand “punishment” to about 2 units on the Karolinska Sleepiness Scale (KSS) [26].

$$R(t) = \begin{cases} R(t-1) - R_c R_d L \Delta t \left(1 - \frac{S(t)+C(t)+U(t)-a_l}{a_u-a_l}\right) & \text{driving} \\ \min(0, R(t-1) + R_c R_r \Delta t) & \text{resting} \end{cases} \quad (6)$$

The modelled fatigue level is defined according to equation (7). The scaling factors approximately transforms the fatigue level to a scale similar to KSS.

$$\text{Fatigue}(t) = 10.9 - 0.6 \left( \frac{S(t) + C(t) + U(t) + W(t) + R(t)}{U(t) + W(t) + R(t)} \right) \quad (7)$$

Note that  $R(t)$  has a minimum value of 0, which means that relaxation without sleep can only recuperate the driver from the task related fatigue that has built up during the drive. To recuperate from sleepiness caused by circadian or homeostatic effects, only sleep will help. All constants in equations (1)–(7) were established empirically in Åkerstedt, et al. [24] and Peng, et al. [25].

### D. Estimation of gained driving time

The gained driving time is set to 0 if the predicted fatigue level, equation (7), in the end of the drive is above the equivalence of  $KSS \geq 7$ . If not, the driver can gain the time it takes to reach  $KSS=7$ , but not more than the sum of two piecewise linear models, equations (8) and (9), and no more than 120 minutes in total. The threshold was set at  $KSS=7$  for several reasons. The verbal anchor of  $KSS 7$  is “sleepy, but no effort to keep awake”, which indicates a moderate but tolerable level of sleepiness. The first signs of objective sleepiness, such as slow eye movements, appearance of alpha waves in the EEG, and decreased vigilance performance, normally starts at  $KSS$  level 7 [26, 27]. Below  $KSS$  level 7, physiological sleep-related signs are rarely seen.

The breakpoints in the linear functions in equations (8) and (9) are based on available research on the recuperating value of resting and napping. There is no strong evidence that a very short rest break reduces fatigue other than for a very brief time [28]. It was therefore decided that relaxation times shorter than 10 minutes should not lead to an extension of the driving time. Rest breaks of 10–20 minutes may temporarily improve performance for a period of about 15–20 minutes [10]. For longer rest breaks of about 30 minutes, there is relatively strong support for reduced fatigue for 30–60 minutes, via decreased time-on-task related fatigue (unless the individual is suffering from sleep deprivation) [11, 12, 14]. A long rest break  $>1h$  will decrease time-on-task related fatigue, but the beneficial effect will be shorter if the driver is sleep deprived [11].

TABLE I  
ANOVA RESULTS (F-VALUES) WITH SIGNIFICANT DIFFERENCES AT THE 0.05 LEVEL (0.005 AFTER BONFERRONI CORRECTION) MARKED WITH \*.

	Relax/Drive df = (1,792)	Gender df = (1,792)	Age df = (4,792)	Participant df = (86,792)
Mean NN	405.03*	0.21	0.63	107.55*
SD NN	1.29	0.04	6.42*	23.17*
RMSSD	23.44*	0.00	1.23	82.58*
SD2	0.58	0.02	11.33*	16.21*
LF	8.16*	2.14	12.75*	6.55*
LF norm	3.47	4.26	5.27*	11.72*
HF	16.45*	0.01	2.45	6.15*
HF norm	175.22*	10.12*	2.58	16.02*
LF/HF	27.96*	10.55*	2.27	13.02*
SampEn	23.37*	7.77	1.57	10.03*

$$gain_{relax}(t) = \begin{cases} 0 & t < 10 \\ 15 + 1.5(t - 10) & 10 \leq t < 20 \\ 30 + 0.375(t - 20) & 20 \leq t < 60 \\ 45 + 0.5(t - 60) & 60 \leq t < 90 \\ 60 & t \geq 90 \end{cases} \quad (8)$$

The beneficial effect of sleep is assumed to be stronger compared to brief rest breaks, and scheduled naps at work has been shown to improve performance and decrease fatigue in shift workers [29]. According to the two-process theory of sleep regulation, recovery is exponential and short sleep episodes (<2 hours) are more recuperative than the last hours of a normal sleep period of 7-8 hours [30]. Since it is not clear if an ultra-short nap reduces fatigue, we require at least 10 minutes of sleep before the driving time is extended. A brief sleep episode of 10-20 minutes has been shown to reduce fatigue during or at the end of the work shift [2-4, 31, 32]. For longer naps of 60-90 minutes the beneficial effects are even stronger and may last up to 8 hours after the nap was terminated [4]. Longer sleep episodes that include both deep sleep and REM sleep reduces fatigue substantially, but will also cause more severe sleep inertia [5]. Exactly how long the beneficial effect of a nap during the work shift lasts is not known and the coefficients in equation (9) are therefore based on the results outlined above in combination with our own experience.

It was decided that extending the driving time beyond 2 hours is undesirable since increased variability of work hours, including occasional longer work shift durations, will disturb the drivers' social life situation and possibly also be harmful for their long-term health [33, 34].

$$gain_{sleep}(t) = \begin{cases} 0 & t < 10 \\ 30 + 3(t - 10) & 10 \leq t < 20 \\ 60 + 1.5(t - 20) & 20 \leq t < 40 \\ 90 + 0.6(t - 40) & 40 \leq t < 90 \\ 120 & t \geq 90 \end{cases} \quad (9)$$

### III. RESULTS

The ANOVA results from the relaxation dataset expectedly showed clear interindividual differences in all HRV metrics

(Table I). There were also clear effects of relaxation versus driving and of age in several metrics (Fig. 2). During relaxation compared to driving, the mean NN-interval was 54 ms longer, RMSSD was 4.3 ms longer, LF was 0.1 ms<sup>2</sup>/Hz higher, HF was 0.2 ms<sup>2</sup>/Hz higher, HF norm was 3.7 % higher, LF/HF was 0.78 units lower and SampEn was 0.08 units higher.

When using the HRV metrics as features in a machine learning setup, the best feature set according to SFFS consisted of gender, age, Mean NN, SD2, LF, LF norm, HF norm, LF/HF and sample entropy (Fig. 3). It is interesting that RMSSD is excluded, given that RMSSD is supposed to represent parasympathetic activity, i.e. rest and relaxation. It is also interesting that gender is included, even though subject-dependent HRV features were used. For subject-independent classification, the corresponding best feature set consisted of gender, SDNN, RMSSD, LF, HF and HF norm.

Accuracy, precision, recall, F1 score and a confusion matrix from cross-validation of the SVM classifiers are provided in Table II and Table III. Note that the relatively high performance-ratings are partly a result of the unbalanced dataset. Also note that the number of false positives (driving classified as relaxation) is low, which reflects the choices made when designing the SVM classifier.

A hypothetical example of the output from the fatigue module, fed with data from the relaxation and sleep algorithms, is provided in Fig. 4. The example to the left shows a driver who has been awake since early morning, but then sleeps from 13.00 to 17.00 to prepare for the night shift that starts at 19.00. After 3h of driving there is a 2h relaxation episode from 22.00 to 00.00 where the driving time is extended by 1h. The relaxation episode effectively resets the time on task effect, bringing the estimated fatigue level down to the base homeostatic, circadian and sleep inertia levels (it cannot go lower than this without actual sleep). From 04.00 to 05.00 the

TABLE II  
PERFORMANCE METRICS FOR THE RELAXATION CLASSIFIER. RESULTS PRESENTED AS MEAN ± SD ACROSS THE 100 REPETITIONS.

	Subject-dependent classification		Subject-independent classification	
	Average score (%)	Range (%)	Average score (%)	Range (%)
Accuracy	88.72±1.84	84.98–93.43	80.10±2.25	75.37–86.19
Recall	91.16±1.95	85.50–95.16	81.17±2.18	76.89–86.97
Precision	96.34±1.67	91.49–100.0	97.45±1.27	94.59–100.0
F1	93.66±1.12	91.26–96.41	88.55±1.44	94.59–92.46

TABLE III  
CONFUSION MATRICES FROM THE RELAXATION CLASSIFIERS. RESULTS PRESENTED AS MEAN ± SD ACROSS THE 100 REPETITIONS.

	Subject-dependent classification		Subject-independent classification	
	Drive	Relaxation	Drive	Relaxation
Drive	177.79±5.01	6.76±3.12	206.66±6.52	5.40±2.67
	Range: 166 – 191	Range: 0 – 16	Range: 191 – 227	Range: 0 – 12
	17.26±3.93	11.19±2.82	47.93±5.59	8.01±2.56
Relaxation	Range: 9 – 29	Range: 5 – 18	Range: 34 – 59	Range: 3 – 14

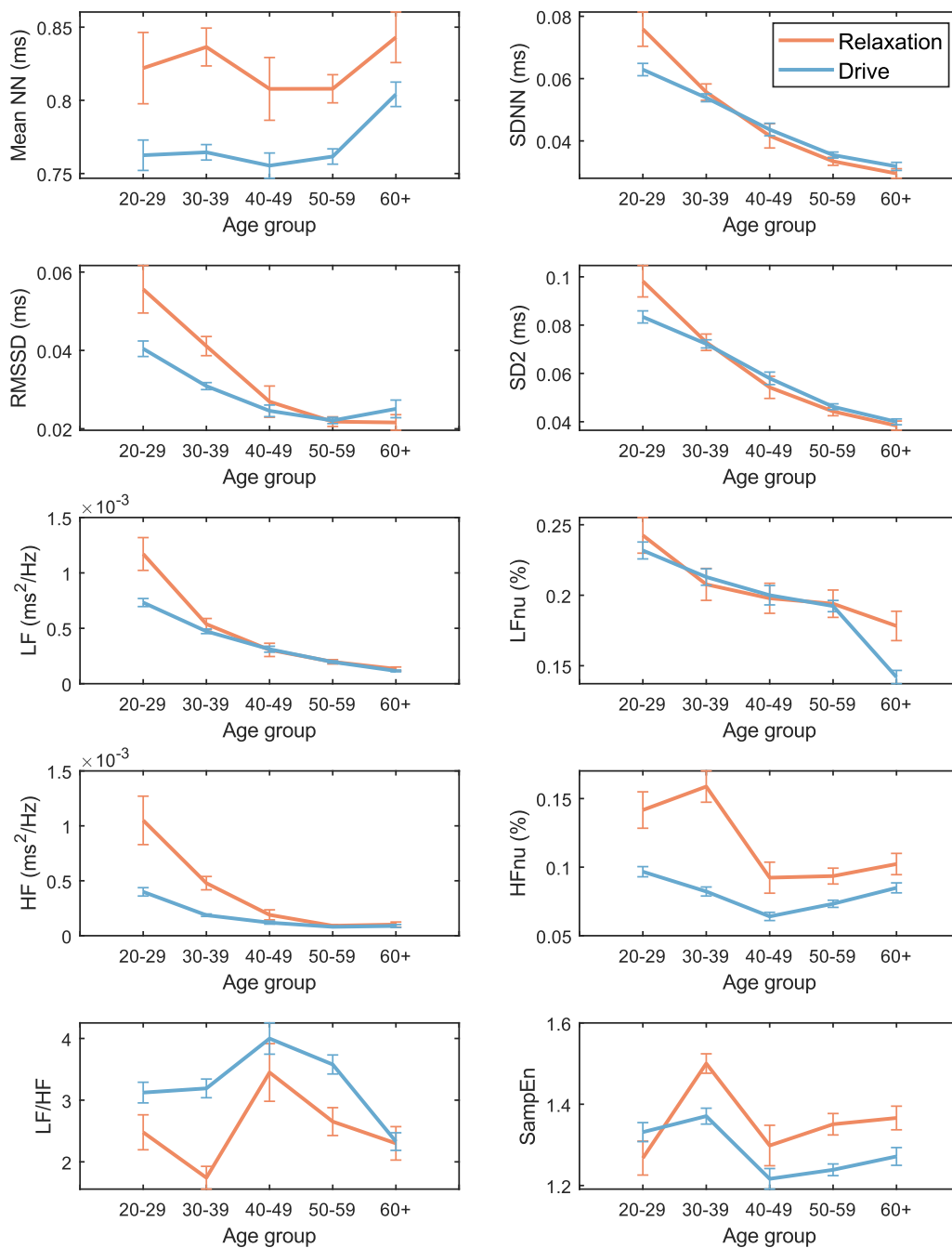


Fig. 2. The mean values of each indicator computed for each of the five age groups for relaxation versus driving. The error bars represent standard error of mean.

driver takes a nap while the automated truck is driving. This allows the driver to continue driving for the maximum extra 2h. The morning nap reduces the estimated fatigue level via the homeostatic component. Note that at the end of the nap (05.00), there is an increase in the estimated fatigue level that is caused by sleep inertia. The blue curve is the estimated fatigue level without any sleep or rest episodes. The difference between the blue and the orange curve is thus reduced fatigue resulting from the rest and sleep episodes. In the example in Fig. 4 (right), the driver did not sleep in the afternoon before the night shift started. The 2h resting period at 22.00 would have led to an extension of the driving time with 60 minutes and the 1h sleep episode at 05.00 would have led to an extension of the driving

time with 102 minutes, totalling 162 minutes according to equations (8) and (9). However, since the gained driving time cannot be longer than 120 minutes, and above all, since the estimated fatigue level is already above the equivalence of  $KSS \geq 7$ , the gained driving time is 0 minutes in this case.

#### IV. DISCUSSION

Automated vehicles have the potential to afford periods of in-cab rest or even sleep, and the overall aim of this paper is to present a first version of a system to effectively manage drive times in highly automated vehicles where sleep and rest are permitted. Another important aim has been to introduce the concept of more flexible drive and rest regulations that takes

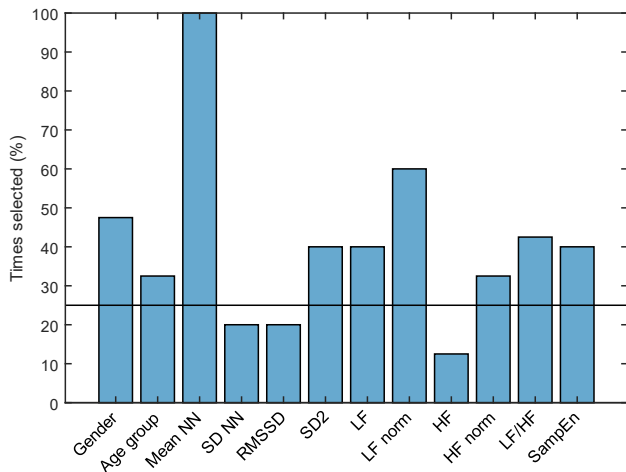


Fig. 3. Percentage of times that the different features were selected in repeated SFFS runs on different partitions of the development set.

automated driving aspects into account. To the best of our knowledge, the main idea behind this work is novel. I.e., is it possible to extend the driving time beyond prescriptive hours of service regulation if the driver has been relaxed and exposed to low levels of stress, or even has slept during the automated drive? If this is possible, the driving task would be less effortful, and the driver could extend working with maximum two hours without increasing safety (accident) risks. The system, assuming that it works, would be a potential useful technological component of fatigue risk management systems that permit greater operational flexibility.

The concept of monitoring whether a driver can rest during work is controversial, not the least from a legal perspective. One of the key challenges is that rest is a complex driver state and the recuperative value depends on the activities that are carried out while resting [12]. The monotony that is characteristic for long-haul truck driving is clearly interrupted for a while, but the consequences for the remains of the drive must be further investigated. It should be noted that this paper is mostly a theoretical contribution and that we have no empirical evidence

that supports that drivers can sleep and obtain high quality recovery during highly automated driving. A thorough validation of the proposed system is thus much needed. Such a study would require experiments where many drivers' fatigue levels are assessed repeatedly over several consecutive workdays. To ensure ecological validity, such a validation study would have to be conducted on public roads, either in a highly automated truck, or for the time being, in a Wizard of Oz setup.

Another significant challenge refers to the real-time measurement of relaxation and sleep. In particular, there are unsolved problems related to personalisation (for example, age and gender play an important role for detection of relaxation) and how to obtain individual information of homeostatic sleep pressure. Whereas robust wearable and non-obtrusive sensors is one part of the solution, problems remain when it comes to time-varying intra-individual variability in the underlying HRV data [23, 35]. Using closed eyes as an indirect measure of sleep also has its problems, for example the difficulties of distinguishing sleep from relaxation with closed eyes, and the inability to assess the quality of sleep. This needs to be addressed in future research. As a first step, counterfactual simulations could be carried out to reveal issues and limitations with the biomathematical model, and to simulate the effects of sensor loss or miss-classifications.

A key assumption of high-quality, recuperative rest is that the indicators should return to baseline levels (i.e. the same level as when work started) when rest is completed [36]. In an automated driving setting, rest via sleep can restore the fatigue level by affecting the homeostatic drive for sleep. However, even if the sleep episode is extended to several hours this will not affect the circadian component, so returning to baseline levels is something that can only be done when considering fatigue and performance over consecutive workdays. Rest via relaxation may in turn revoke the negative effects of stress or task-related fatigue on neurobehavioral function, if the increase in stress due to driving was small to moderate.

Based on the literature of sleep and rest breaks as

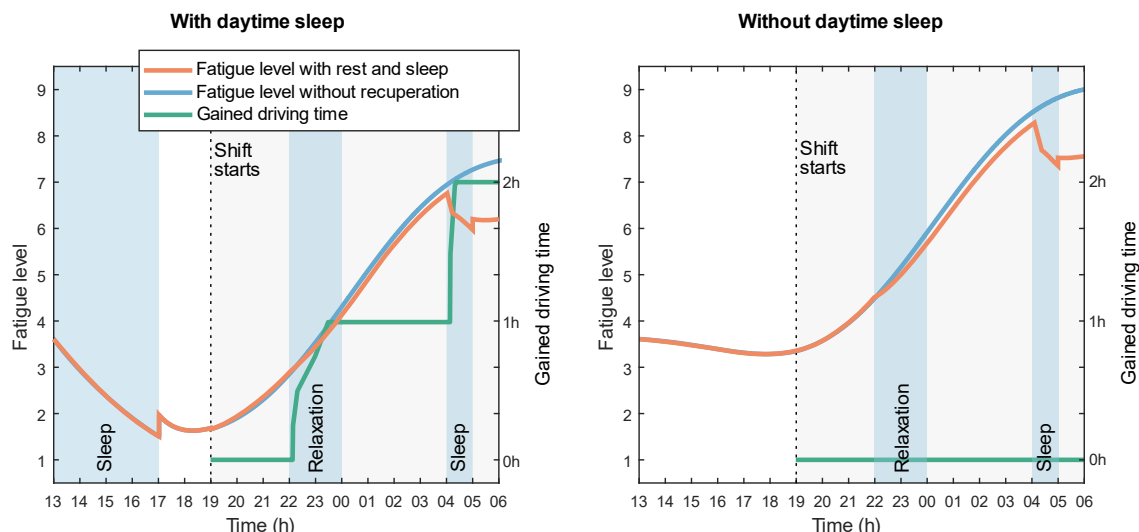


Fig. 4. Two examples of estimated fatigue level and gained driving time. Left: The driver has been awake since early morning and starts driving at 19.00. After 2h of driving there is a 2h rest episode from 22.00 to 00.00. From 04.00 to 05.00 the driver is taking a nap. Right: Same as left, but the driver also slept from 13.00 to 17.00 in the afternoon.

countermeasures of fatigue and performance decrements, we have estimated the potential beneficial effects on alertness in terms of maintaining adequate work performance for an extended period of time. However, a hybrid solution based on a combination of prescriptive hours of service regulation with a more flexible risk management approach is probably needed in order to obtain stakeholders' and drivers' acceptance, as well as to avoid too demanding work hours [1, 34]. Also, it should be noted that the prescriptive hours of service-approach, which regulates maximum shift duration, rest time between shifts, and rest-breaks within the work shift, has limitations and it is very difficult to define rules that take circadian and long-term sleep loss into account [1].

Further development of the presented system needs more basic research on whether it is possible to relax during highly automated driving, how relaxation should be measured during driving, and how long the beneficial effects of rest remains when relaxation and sleep no longer occurs. One important modifying factor is the activity during the break. If the driver is engaged in mentally demanding (stressful) activities the beneficial effects might be weaker, even though there is very limited research on type of activity and recovery during a rest break. Intake of caffeine during the break may increase the beneficial effects and drinking coffee may for some individuals be as effective as a nap [2].

There are knowledge gaps of the effectiveness of napping at various circadian phases and we decided to not take time-of-day into account when we estimated the effect of sleep during automated driving. Furthermore, it is important to gain further knowledge on the effects of sleep inertia on driving performance when the driver has to handle a take over from automatic mode to manual driving. Other limitations that needs to be addressed include that (i) the relaxation algorithm was developed on passenger car drivers whereas the target application is long-haul trucking, and (ii), that the full system needs to be evaluated in a naturalistic setting with highly automated trucks and with drivers experienced with automated driving, especially when it comes to the amount of gained driving time.

## V. CONCLUSIONS

An algorithm that adapts the driving time and rest periods during automated driving has been developed. The algorithm accounts for driver state by measuring relaxation and sleep in real-time. The recuperative value of sleep and relaxation are considered, but not the situation "doing something else". Further research is needed to test the full system and to investigate the long-term consequences of extended driving times, including user acceptance of the key stakeholders. Further research is also needed on how the gained driving time output is best communicated to the driver, and how this time should be logged and accounted for in the electronic record of duty status.

During the current period of disruption to the automotive industry, there are several potential applications of the work reported here. At its core, we envision such technology to support long-haul truck driving applications that include a

mixture of autonomous and manual driving. An example use case could involve driving from a port city over multiple days to various urban or regional centers where automated driving is either not possible for the full duration of the journey (due either to technical limitation or legislative boundaries).

## ACKNOWLEDGMENT

We gratefully acknowledge Clara Berlin (VTI), Christian Forsberg and Johan Karlsson (Autoliv) for their work related to the relaxation experiment, and Torbjörn Åkerstedt and Phil Tucker at the Stress Research Institute for valuable insights in the early stages of this project.

## REFERENCES

- [1] K. A. Honn, H. P. Van Dongen, and D. Dawson, "Working Time Society consensus statements: Prescriptive rule sets and risk management-based approaches for the management of fatigue-related risk in working time arrangements," *Industrial health*, pp. SW-8, 2019.
- [2] L. A. Reyner and J. A. Horne, "Suppression of sleepiness in drivers: combination of caffeine with a short nap," *Psychophysiology*, vol. 34, no. 6, pp. 721-725, 1997.
- [3] M. Takahashi, "The role of prescribed napping in sleep medicine," *Sleep medicine reviews*, vol. 7, no. 3, pp. 227-235, 2003.
- [4] G. Ficca, J. Axelsson, D. J. Mollicone, V. Muto, and M. V. Vitiello, "Naps, cognition and performance," *Sleep medicine reviews*, vol. 14, no. 4, pp. 249-258, 2010.
- [5] C. J. Hilditch, J. Dorrian, and S. Banks, "A review of short naps and sleep inertia: do naps of 30 min or less really avoid sleep inertia and slow-wave sleep?," *Sleep Medicine*, vol. 32, pp. 176-190, 2017.
- [6] E. J. Silva and J. F. Duffy, "Sleep inertia varies with circadian phase and sleep stage in older adults," *Behavioral neuroscience*, vol. 122, no. 4, p. 928, 2008.
- [7] D. F. Dinges, M. T. Orne, and E. C. Orne, "Assessing performance upon abrupt awakening from naps during quasi-continuous operations," *Behavior Research Methods, Instruments, & Computers*, vol. 17, no. 1, pp. 37-45, 1985.
- [8] J. Wörle, B. Metz, C. Thiele, and G. Weller, "Detecting sleep in drivers during highly automated driving: the potential of physiological parameters," *IET Intelligent Transport Systems*, 2019.
- [9] M. Hirsch, F. Diederichs, H. Widlroither, R. Graf, and S. Bischoff, "Sleep and take-over in automated driving," *International journal of transportation science and technology*, vol. 9, no. 1, pp. 42-51, 2020.
- [10] M. Sallinen *et al.*, "Recovery of cognitive performance from sleep debt: Do a short rest pause and a single recovery night help?," *CHRONOBIOLOGY INTERNATIONAL*, vol. 25, no. 2-3, pp. 279-296, 2008.
- [11] J. O. Phipps-Nelson, J. R. Redman, and S. M. W. Rajaratnam, "Temporal profile of prolonged, night-time driving performance: breaks from driving temporarily reduce time-on-task fatigue but not sleepiness," *Journal of Sleep Research*, vol. 20, no. 3, pp. 404-415, 2011.
- [12] P. Tucker, "The impact of rest breaks upon accident risk, fatigue and performance: a review," *Work & Stress*, vol. 17, no. 2, pp. 123-137, 2003.
- [13] M. R. Stevenson *et al.*, "The role of sleepiness, sleep disorders, and the work environment on heavy-vehicle crashes in 2 Australian states," *American journal of epidemiology*, vol. 179, no. 5, pp. 594-601, 2013.
- [14] P. Tucker, S. Folkard, and I. Macdonald, "Rest breaks and accident risk," *The Lancet*, vol. 361, no. 9358, p. 680, 2003.
- [15] R. Phillips, G. Kecklund, A. Anund, and M. Sallinen, "Fatigue in transport: a review of exposure, risks, checks and controls," *Transport reviews*, vol. 37, no. 6, pp. 742-766, 2017.
- [16] J. F. May and C. L. Baldwin, "Driver fatigue: The importance of identifying causal factors of fatigue when considering detection and countermeasure technologies," *Transportation Research Part F: Psychology and Behaviour*, vol. 12, no. 3, pp. 218-224, 2009.

- [17] J. S. Ruggiero and N. S. Redeker, "Effects of napping on sleepiness and sleep-related performance deficits in night-shift workers: a systematic review," *Biological research for nursing*, vol. 16, no. 2, pp. 134-142, 2014.
- [18] (2020, February 18). *ADAS&ME*. Available: <https://www.adasandme.com/>
- [19] V. X. Afonso, W. J. Tompkins, T. Q. Nguyen, and S. Luo, "ECG beat detection using filter banks," *IEEE Transactions on biomedical engineering*, vol. 46, no. 2, pp. 192-202, 1999.
- [20] M. Karlsson, R. Hörnsten, A. Rydberg, and U. Wiklund, "Automatic filtering of outliers in RR intervals before analysis of heart rate variability in Holter recordings: a comparison with carefully edited data," *Biomedical engineering online*, vol. 11, no. 1, p. 2, 2012.
- [21] F. Shaffer and J. Ginsberg, "An overview of heart rate variability metrics and norms," *Frontiers in public health*, vol. 5, p. 258, 2017.
- [22] P. Pudil, "Floating Search Methods in Feature Selection," *Pattern Recognition Letters*, pp. 1119 - 1125, 1994.
- [23] M. Lohani, B. R. Payne, and D. L. Strayer, "A Review of Psychophysiological Measures to Assess Cognitive States in Real-world Driving," *Frontiers in Human Neuroscience*, vol. 13, p. 57, 2019.
- [24] T. Åkerstedt, J. Connor, A. Gray, and G. Kecklund, "Predicting road crashes from a mathematical model of alertness regulation—The Sleep/Wake Predictor," *Accident Analysis & Prevention*, vol. 40, no. 4, pp. 1480-1485, 2008/07/01/ 2008.
- [25] H. T. Peng, F. Bouak, W. Wang, R. Chow, and O. Vartanian, "An improved model to predict performance under mental fatigue," *Ergonomics*, vol. 61, no. 7, pp. 988-1003, 2018.
- [26] T. Åkerstedt and M. Gillberg, "Subjective and objective sleepiness in the active individual," *International Journal of Neuroscience*, vol. 52, no. 1-2, pp. 29-37, // 1990.
- [27] T. Åkerstedt, A. Anund, J. Axelsson, and G. Kecklund, "Subjective sleepiness is a sensitive indicator of insufficient sleep and impaired waking function," *Journal of Sleep Research*, vol. 23, no. 3, pp. 240-252, 2014.
- [28] D. F. Neri, R. L. Oyung, L. M. Colletti, M. M. Mallis, P. Y. Tam, and D. F. Dinges, "Controlled Breaks as a Fatigue Countermeasure on the Flight Deck," *Aviation, space, and environmental medicine*, vol. 73, no. 7, pp. 654-664, 2002.
- [29] C. Martin-Gill *et al.*, "Effects of napping during shift work on sleepiness and performance in emergency medical services personnel and similar shift workers: a systematic review and meta-analysis," *Prehospital emergency care*, vol. 22, no. sup1, pp. 47-57, 2018.
- [30] P. Achermann, "The two-process model of sleep regulation revisited," *AVIATION SPACE AND ENVIRONMENTAL MEDICINE*, vol. 75, no. 3, pp. A37-A43, 2004.
- [31] D. Leger, P. Philip, P. Jarriault, A. Metlaine, and D. Choudat, "Effects of a combination of napping and bright light pulses on shift workers' sleepiness at the wheel: a pilot study," *Journal of sleep research*, vol. 18, no. 4, pp. 472-479, 2009.
- [32] C. N. Watling, S. S. Smith, and M. S. Horswill, "Stop and revive? The effectiveness of nap and active rest breaks for reducing driver sleepiness," *Psychophysiology*, vol. 51, no. 11, pp. 1131-1138, 2014.
- [33] A. Arlinghaus, P. Bohle, I. Iskra-Golec, N. Jansen, S. Jay, and L. Rotenberg, "Working Time Society consensus statements: Evidence-based effects of shift work and non-standard working hours on workers, family and community," *Industrial health*, vol. 57, no. 2, pp. 184-200, 2019.
- [34] G. Costa, S. Sartori, and T. Åkerstedt, "Influence of flexibility and variability of working hours on health and well-being," *Chronobiology international*, vol. 23, no. 6, pp. 1125-1137, 2006.
- [35] A. Persson, H. Jonasson, I. Fredriksson, U. Wiklund, and C. Ahlström, "Heart Rate Variability for Classification of Alert Versus Sleep Deprived Drivers in Real Road Driving Conditions," *IEEE Transactions on Intelligent Transportation Systems*, 2020.
- [36] S. A. Geurts and S. Sonnentag, "Recovery as an explanatory mechanism in the relation between acute stress reactions and chronic health impairment," *Scandinavian journal of work, environment & health*, pp. 482-492, 2006.

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