# *The Intelligent Power Nap System for Restoring Behavioral Capabilities in Sleepy Drivers*

1st Shao-Yang Cheng
*Department of Computer Science and Information Engineering*
*National Cheng Kung University*
Tainan, Taiwan
p76134139@gs.ncku.edu.tw

2nd Xun-Meie Kuo
*Department of Computer Science and Information Engineering*
*National Cheng Kung University*
Tainan, Taiwan
zxc880214@gmail.com

3rd Chih Hsiang Tsai
*Department of Engineering Science*
*National Cheng Kung University*
Tainan, Taiwan
motomomo123@gmail.com

4th Shih-Wei Chang
*Department of Computer Science and Information Engineering*
*National Cheng Kung University*
Tainan, Taiwan
ben0800092000@gmail.com

5th Tsung-Hao Hsieh
*Department of Computer Science*
*Tunghai University*
Taichung, Taiwan
thhsieh@thu.edu.tw

6th Yu-Kai Wang
*Faculty of Engineering and Information Technologies*
*University of Technology Sydney*
Sydney, New South Wales, Australia
yukai.wang@uts.edu.au

7th Sheng-Fu Liang
*Department of Computer Science and Information Engineering*
*National Cheng Kung University*
Tainan, Taiwan
sfliang@mail.ncku.edu.tw

***Abstract*—Drowsiness significantly increases the risk of accidents and degrades the driver's performance by reducing attention and concentration. Various fatigue driving detection studies and technologies have been proposed, but few of them have thoroughly assessed the efficacy of sleep-based recovery techniques. This study investigates whether a controlled Power Nap may successfully improve fatigue-related driving performance. A total of 10 participants responded to lane deviation events throughout three sessions of driving in a driving simulator, which are regular driving, fatigue driving brought on by extended cognitive demands and post-rest driving conducted after finishing both the fatigue driving session and a controlled Power Nap. Lane deviation events were simulated by controlled steering wheel perturbation. Subjects' reaction time to lane deviation events were used as an indicator of fatigue level. We minimized sleep inertia by monitoring sleep stages and ensuring naps stayed in non-deep sleep phases using an EEG-based Powernap mobile application. Statistical analysis revealed a significant increase in reaction time after fatigue induction ($t(9) = 10.99$, $p < 0.001$), and a significant reduction following the Power Nap ($t(9) = 8.26$, $p < 0.001$). The results show that the suggested mobile nap system successfully lowered reaction times to nearly normal levels. These results support the idea that short, controlled naps that follow the Intelligent Rest Strategies can speed up recuperation from sleep-related exhaustion and improve road safety.**

***Keywords—fatigue recovery, power nap, EEG, intelligent rest strategy***

## I. Introduction

Fatigue and drowsiness are two of the main causes of driving accidents. According to the National Center for Statistics and Analysis, 697 fatalities in the United States in 2019 were attributed to fatigue-related crashes, accounting for approximately 1.9% of all traffic deaths [1]. Accidents are more likely to occur when drivers are sleepy or exhausted because their reaction time, focus, and ability to make decisions are all much worse than when they are completely awake [2]. Even though fatigue detection is a feature of many modern driver assistance systems, these systems mostly use objective indications and offer alerts to detect drowsiness. They don't solve the fundamental issue of regaining alertness. Developing a quick and efficient rest strategy that allows drivers to return to normal performance levels in both objectively and subjectively fatigued states is crucial to reducing the risks associated with fatigue driving. This will encourage drivers to take restorative breaks and increase road safety for all users.

Numerous fatigue detection techniques have been proposed, such as EEG-based power spectral density (PSD) analysis [3], heart rate variability (HRV) monitoring [4] and percentage of eyelid closure (PERCLOS) measurements [5]. EEG-based PSD detects fatigue through the decreased high-frequency power and increased low-frequency power (θ, α, and δ bands). HRV reflects autonomic nervous system changes associated with wakefulness to sleep. PERCLOS measures the eyelid closure duration, which correlates with EEG markers of weariness. These methods are useful for identifying drowsiness, but none of them deal with recovery after fatigue.

On-line sleep-stage monitoring offers a promising solution for fatigue recovery. Power Nap is a kind of brief nap limited to stage N2 of non-rapid eye movement (NREM) sleep , while avoiding progression into stage N3 sleep (slow wave sleep) [6] [7]. Maintaining sleep within stage N2 can restore both subjective alertness and objective cognitive function to levels that are close to performance under alert conditions, and avoiding progression into stage N3 helps prevent the sleep inertia [8], which is a temporary decline in performance upon waking. EEG-based sleep monitoring makes it possible to precisely time naps to minimize sleep inertia and optimize recovery benefits.

According to the above survey, this paper aims to investigate whether an intelligent power nap can improve the behavioral performance of sleepy drivers. In a driving simulator, we evaluate each driver's performance under three different scenarios: normal (alert) driving, fatigue driving induced by cognitive tasks, and post-rest driving following a Power Nap under an intelligent rest protocol directed by EEG-based sleep stage monitoring. Reaction time was measured as the main performance parameter using lane deviation events that were simulated by controlled steering wheel perturbations. We evaluate whether an on-line EEG-guided power nap system, can effectively reverse the behavioral impairments caused by driver fatigue, and provide a practical solution to enhance driving safety.

## II. METHODS

The experiment was designed into five sequential stages as shown in Fig. 1: baseline (alert) driving, sudoku-based fatigued induction, fatigued driving, power nap rest intervention, and post-rest driving. In the baseline stage, participants completed a 15 minutes driving simulation under well-rested conditions to create reference driving performance. In the sudoku-based fatigue induction stage, participants was required to play sudoku puzzles continuously until they felt tired for a maximum duration of one hour. In the fatigue driving stage, participants completed the same driving simulation right after completing the fatigue induction task. The power nap stage offered a short, EEG-guided nap to promote recovery and avoid the onset of deep sleep and sleep inertia. Lastly, in the post-rest driving stage, participants repeated the driving simulation under the same condition as baseline and fatigue driving stages. Before the start of each driving session, participants completed Stanford sleepiness scale (SSS) [9] to assess their objective alertness level.

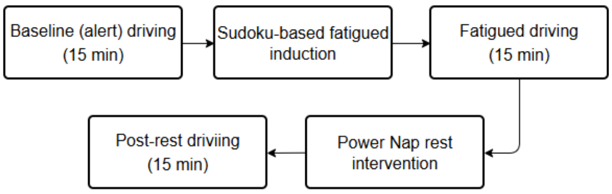



Fig. 1. Experimental design.

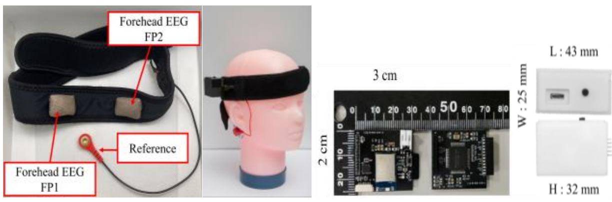
A fixed-base driving simulator developed with the CARLA [10] driving simulation tools was used to carry out the experiment. In order to enable realistic driving control, the system was equipped with an actual steering wheel, an accelerator, and a brake pedal. The maximum vehicle speed in the simulation was set at 60 kilometer per hour to maintain consistent driving conditions and lower the possibility of large performance variability brought on by excessive speed. To ensure that participants could concentrate only in lane-keeping without outside distractions, the virtual driving environment was created as a long straight road network with very few turns, no obstacles, and no surrounding traffic. The visual environment and steering wheel interface of driving simulator are shown in Fig. 2

(a) (b)

Fig. 2. The driving simulator insterface (a) showing the visual environment during the task and (b) a participant performing the driving simulation task using a fixed-base simulator with a steering wheel interface.

The duration of each driving simulation session was 15 minutes. A steering wheel deviation event was initiated after a random period of time. In the steering wheel deviation scenario, the virtual vehicle would drift laterally toward the roadside in the simulated world as a result of a programmed steering-wheel offset. The participant would have to counter-steer and bring the virtual car back to the center of the lane. Over the course of driving simulation, there were roughly 10 to 15 deviation instances every session. Participants' reaction times were measured as the interval between the deviation onset and the initiation of corrective steering, and later analyzed to quantify driving performance under baseline, fatigued, and post-rest conditions.

The intelligent power nap was designed to maximize recovery and avoid sleep inertia. The nap duration was limited to 30 minutes. The goal of the nap was to sleep int and sustain in non-rapid eye movement stage 2 sleep (N2), which is linked to the efficient cognitive recovery. To monitor sleep stages in real time, participants wore an EEG headband device that does not interfere with nap. The headband embeds EEG electrodes and contains a sensing module as shown in Fig. 3, consisting of an nRF52840 microchip unit and an ADS1299 analog front-end. The detailed specifications are shown in Table 1.




(A) (B) (C) (D)

Fig. 3. Design of headband. (A) The headband contains two EEG channels (FP1, FP2) and a reference; (B) Wearing diagram and circuits of the wireless physiological measurement module (C)Top board circuit with MCU, USB plugin, SD card, and other parts; Bottom board with ADC and signal input pin; (D) Packaging with battery for wearable device.

TABLE I. SPECIFICATIONS OF THE PORTABLE WIRELESS EEG MEASUREMENT MODULE

| *Item* | *PID* | *Function* |
|---|---|---|
| MCU | nRF52840 | Frequency: 2.4 GHz<br>RAM: 256 kB<br>Microcontroller: ARM Cortex-M4F<br>Bluetooth: 5.0 |
| ADC | ADS1299 | 4 channels Resolution: 24 Bits<br>Sample rate: 250 Hz ~ 16 kHz<br>Input range (V): 0–5.25<br>Gain: 1–24 |

On-line sleep staging was performed using a decision tree algorithm based on the 2020 guidelines of the American Academy of Sleep Medicine (AASM), as illustrated in Fig. 4. The algorithm classified each 30 second epoch into one of five sleep stages based on distinctive EEG patterns. Features of stage classification is shown in Table 2. Stage wake was identified when there were noticeable eye blinks or movement artifacts in the EEG signals, or when a dominant alpha rhythm (8 – 12 Hz) persisted for more than 50% of the epoch (i.e., ≥15 seconds). Alpha activity that persisted for less than half of the epoch was considered to be in stage N1. N1 stage, which had a diminished but still detectable alpha rhythm, symbolized the period between wakefulness and sleep. Stage N2 was marked by the appearance of sleep spindles (12 − 15 Hz with a duration ≥0.5 seconds), the presence of slow waves (SW) lasting up to 6 seconds, or by a continuation of N2 when no other stage-specific features were identified in the current epoch. Stage N3, or deep sleep, was detected when slow waves in the 0.5–2 Hz frequency range with a peak-to-peak amplitude exceeding 75 µV accounted for more than 20% of the epoch duration (i.e., over 6 seconds). This staging algorithm ensured the best possible recovery while preventing sleep inertia by enabling real-time classification and adaptive wake-up scheduling based on the participant's current sleep depth. The power nap app monitored incoming data in real time and updated sleep stage predictions continuously. If N2 sleep was detected and sustained, the nap was allowed to continue. If deeper stages (e.g., N3) were approached or the nap exceeded the 30 minute limit, the system initiated a wake-up alert to avoid sleep inertia and preserve post-nap cognitive performance.

TABLE II. FEATURES OF STAGE CLASSIFICATION

| *No* | *Feature* | *Label* |
|---|---|---|
| 1 | Alpha duration (8-12 Hz) | Alpha |
| 2 | SW duration (0.5-2 Hz) | SW |
| 3 | Spindle number (12-15 Hz) | Spindle num |
| 4 | Eye blinking number | Eye blink |
| 5 | Line length in a window (1 s) | Artifact |

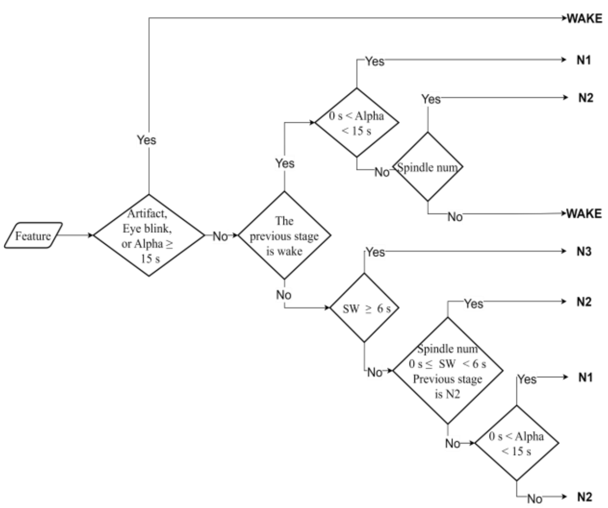



Fig. 4. Decision tree model structure for sleep stage classification.

## III. RESULTS

To evaluate the effectiveness of Power Nap as a fatigue recovery strategy in driving simulation, both behavioral and physiological data were analyzed.

Figure 5 displays Subject 10's steering angle over time during a deviation event in the baseline (alert), fatigue, and post-rest condition. All charts share a 1.5-second observation window starting from the moment of deviation onset. In the baseline condition, the subject started corrective steering at approximately 0.30 seconds, returned to lane center smoothly and under control. The deviation angle of steering wheel peaked at about 15 degrees, and rapidly stabilized. In the fatigued condition, the participant showed a delayed onset of response, with corrective steering starting at 0.55 to 0.60 seconds. Due to the delayed reaction, the steering-wheel deviation caused by the programmed drift reached nearly 180 degrees before any corrective movement was made, which suggests delayed perception and decreased motor control. In the post-rest condition, the response improved considerably. Corrective steering resumed earlier (around 0.30 seconds) with a moderate peak around 30 degrees, indicating the recovery of reaction timing and control precision. These results imply that power nap contributes to the recovery of both reaction latency and correction accuracy.

Reaction time is the main behavioral metric, and defined as the amount of time that passed between the beginning of a steering-wheel deviation and the participant's initiating a corrective steering movement to bring the vehicle back to the lane center. For each participant, reaction time was recorded at three distinct experimental stages, with each stage reaction time represented as follows:

$$T_b = Baseline\ stage\ reaction\ time\ (sec) \quad (1)$$

$$T_f = Fatigued\ stage\ reaction\ time\ (sec) \quad (2)$$

$$T_r = Postrest\ stage\ reaction\ time\ (sec) \quad (3)$$

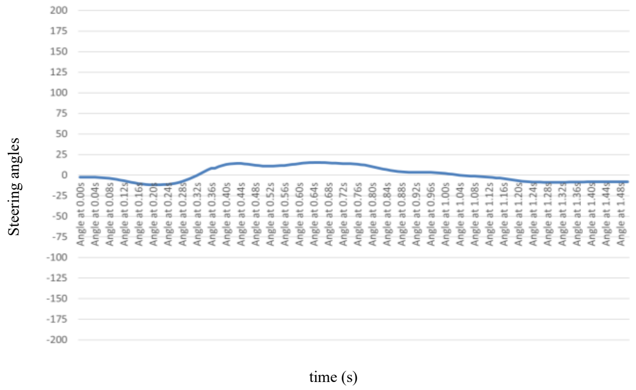
The following two indices were computed to measure performance variations across stages. TIME_INC represents the proportional increase in reaction time due to fatigue. A higher TIME_INC indicates a greater performance decline. TIME_DEC reflects the degree of recovery after the power nap intervention. A larger TIME_DEC indicates greater improvement in alertness and reaction time.

$$TIME\_INC = \frac{T_f - T_b}{T_b} \quad (4)$$

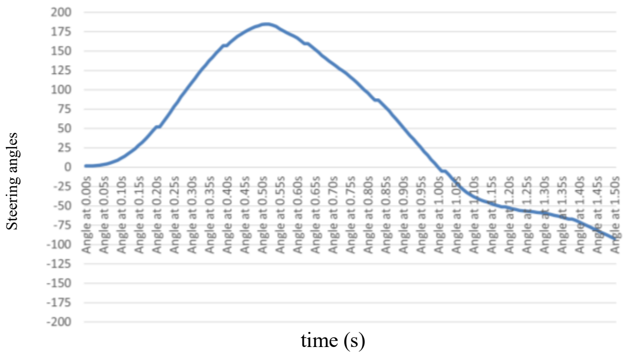
$$TIME\_DEC = \frac{T_f - T_r}{T_r} \quad (5)$$

The full dataset across ten participants was analyzed to evaluate the effects of fatigue and power nap recovery strategy on driving performance. Three key metrics were used: reaction time during baseline (Tb), fatigued (Tf), and post-rest (Tr) conditions; Stanford Sleepiness Scale (SSS) scores were also collected before each driving phase: baseline (Sb), fatigued (Sf), and post-rest (Sr) conditions. The sleep onset latency (SOL), which is eye close for read to N1 stage, was also estimated during the power nap according to the EEG recordings.

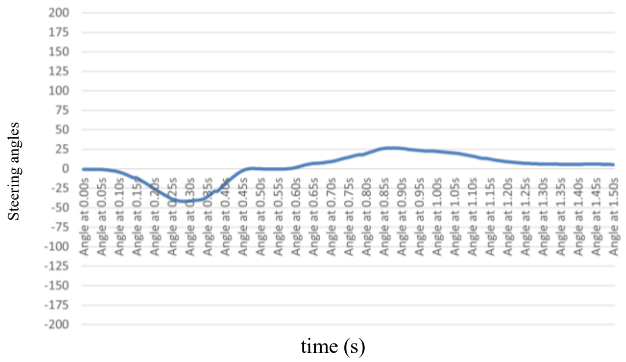
Positive TIME_INC results showed that individuals had slower reaction times after the fatigue induction phase. This implies that the Sudoku task was typically successful in inducing fatigue. After the power nap intervention, reaction times decreased compared to the fatigue stage as TIME_DEC values were positive. Those who suffered more fatigue-related decrease, such Subject 04, who had a 53% TIME_INC and a 91% TIME_DEC, showed the strongest recovery. This suggests that power nap resting strategy could work even for people who are experiencing extreme states of fatigue.




(a)




(b)




(c)

Fig.5. Steering angle over time for Subject 10 during a single deviation event in (a) the baseline condition, (b) the fatigue condition and (c) the post-rest condition.

The comparison of average reaction time between baseline (Tb) and fatigued (Tf) conditions revealed a significant increase (paired t-test, $t(9) = 10.99$, $p < 0.001$), indicates a strong effect of fatigue on reaction time. Reaction times after the power nap (Tr) were significantly lower than those during the fatigued condition (Tf) (paired t-test, $t(9) = 8.26$, $p < 0.001$), indicating that the rest intervention effectively improved behavioral response speed.

TABLE III. Behavioral, subjective, and physiological indicators of fatigue and recovery for all participants

| No | Baseline | | Fatigue | | | Post-rest | | | |
|---|---|---|---|---|---|---|---|---|---|
| | *Tb* | *Sb* | *Tf* | *Sf* | *SOL* | *Tr* | *Sr* | *TIME INC* | *TIME DEC* |
| **1** | .59 | 4 | .76 | 6 | 8.5 | .56 | 3 | 29% | 34% |
| **2** | .36 | 3 | .57 | 5 | 2.5 | .44 | 3 | 56% | 36% |
| **3** | .46 | 2 | .66 | 6 | 7 | .35 | 3 | 44% | 67% |
| **4** | .49 | 3 | .74 | 5 | 5 | .30 | 3 | 53% | 91% |
| **5** | .41 | 3 | .56 | 4 | 1.5 | .37 | 2 | 39% | 49% |
| **6** | .54 | 3 | .66 | 4 | >20 | .39 | 3 | 23% | 50% |
| **7** | .61 | 3 | .80 | 4 | 2 | .64 | 3 | 31% | 27% |
| **8** | .49 | 4 | .82 | 5 | 5 | .49 | 3 | 67% | 67% |
| **9** | .62 | 3 | .82 | 4 | 2.5 | .48 | 3 | 32% | 55% |
| **10** | .48 | 3 | .66 | 5 | 0.5 | .47 | 3 | 38% | 39% |

a. Tb, Tf, and Tr represent average reaction times (in seconds) during the baseline (alert), fatigued, and post-rest phases, respectively. Sb, Sf, and Sr indicate subjective sleepiness scores (Stanford Sleepiness Scale, 1 = most alert to 7 = very sleepy) collected before each phase. SOL (min) refers to the time required to enter stage N1 sleep during the power nap session. TIME_INC and TIME_DEC are calculated as the proportional change in reaction time due to fatigue and recovery, respectively.

## IV. Discussions

In this study, we demonstrated that drivers suffering from cognitive fatigue can successfully resume their behavioral performance after taking a short power nap followed by intelligent rest strategies. Using a combination of simulated driving tasks, subjective sleepiness assessments, and EEG-based sleep monitoring, the experiment results showed that reaction time significantly increased after fatigue induction and was successfully reduced after a short rest intervention. There was a high correlation between the degree of recovery (TIME_DEC) and the fatigue-induced performance decrease (TIME_INC), suggesting that the power nap was beneficial even for those who were affected by heavy fatigue. Standford sleepiness scores (SSS) generally aligned with objective behavioral impairments, and also subjectively inducted the effectiveness of power nap for alertness recovery. These results suggest that implementing intelligent, time-efficient rest strategies like power nap could be a practical and expandable solution to reduce the risks associated with drowsiness driving.

## Acknowledgment

This work was supported in part by the National Science and Technology Council, Taiwan, under Grant NSTC 113-2221-E-006-168, 114-2221-E-006-150 and in part by the Higher Education Sprout Project, Ministry of Education at National Cheng Kung University.

## References

[1] National Center for Statistics and Analysis. Overview of motor vehicle crashes in 2019: Traffic safety facts research note. Report no. dot hs 813060.

[2] Vanlaar, W., Simpson, H., Mayhew, D., & Robertson, R. (2008). Fatigued and drowsy driving: A survey of attitudes, opinions and behaviors. *Journal of Safety Research*, *39*(3), 303–309.

[3] Arefnezhad, S., Hamet, J., Eichberger, A., Frühwirth, M., Ischebeck, A., Koglbauer, I. V., Moser, M., & Yousefi, A. (2022). Driver drowsiness estimation using EEG signals with a dynamical encoder–

decoder modeling framework. *Scientific Reports, 12,* Article number: 2650.

[4] Fujiwara, K., Abe, E., Kamata, K., Nakayama, C., Suzuki, Y., & Yamakawa, T. (2018). Heart rate variability-based driver drowsiness detection and its validation with EEG. *IEEE*.

[5] Majumder, S., Guragain, B., Wang, C., & Wilson, N. (2019). On-board Drowsiness Detection using EEG: Current Status and Future Prospects. *IEEE*.

[6] Kuo,X.-M.(2023). Effects of Power Nap on Sleepiness Relief and Cognitive Performance Recovery in Sleepy People (Master Thesis). National Cheng Kung University, R.O.C.,Tainan.

[7] Liang, S., Shih, Y., Hu, Y., & Kuo, C. (2020). A method for napping time recommendation using electrical brain activity. *IEEE Transactions on Cognitive and Developmental Systems*, *12*(3), 645–657.

[8] Tassi, P., & Muzet, A. (2000). Sleep inertia. Sleep medicine reviews, 4(4), 341-353.

[9] Hoddes, E., Zarcone, V., Smythe, H., Phillips, R., & Dement, W. C. (1973). Quantification of sleepiness: a new approach. Psychophysiology, 10(4), 431-436.

[10] Dosovitskiy, A., Ros, G., Codevilla, F., López, A. M., & Koltun, V. (2017). CARLA: an open urban driving simulator. *Conference on Robot Learning*, 1–16.