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THE DEVELOPMENT OF COGNITIVE WORKLOAD MANAGEMENT FRAMEWORK BASED ON NEURONAL DYNAMICS PRINCIPLE TO MAINTAIN TRAIN DRIVER'S HEALTH AND RAILWAY SAFETY

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Abstract

Fatigue increases the tendency of poor train driving strategy decision. Decision making in cognitive overload and cognitive underload situation mostly outputs bad decisions. Accordingly, train driver's cognitive function is required to be sTable during travel so that they can give correct response at a given situation. This study constructs a conceptual framework for cognitive workload management (CWM) of train driver by taking the energy expenses from cognition into the account. This study combines objective and subjective cognitive workload analysis to evaluate train driver duty readiness. The objective load analysis was performed through energy level approximation based on neuronal dynamics simulation from 76 brain regions. The cognitive energy expenditure (CEE) calculated from neuron action potential (NAP) and the ion-membrane current (IMC) from the simulation results. The cognitive load (CL) approximated by converts the continuous time-based CEE to discrete frequency-based CL using Fourier series. The subjective cognitive workload obtained from train simulation results followed by 27 participants. The participants fill the questionnaire based on their simulated journey experience. The results of the evaluation used to build readiness evaluation classifier based on control chart. The control chart evaluation helps the management to determine weekly rest period and daily short rest period treatment base on each train driver workload. The CWM framework allows different recovery treatment to be applied to each train driver. The impact of the CWM application is the performance of train drivers are kept stable. Thus, the CWM framework based on CEE is useful to prevent physical and mental fatigue.

Keywords: cognitive load, neuronal-dynamics, brain simulation, cognitive energy expenditure, train drivers.

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1. Introduction

The human factor (HF) is a safety-contributing factor in non-autonomous land transportation such as a train. Reportedly, HF accounts for 37 % railway accidents in United States and 27 % in Indonesia from 2005 to 2020 [1, 2]. The data confirms that railway safety is tied to train driver HF. The link between railway safety and HF is the decision. Mainly, train drivers have to decide driving strategy while driving. The train driving process requires train drivers to perform cognitive tasks. Hence, maintaining focus throughout the journey is mandatory to ensure a train driver makes the correct decision. A usual strategy to maintain train driver focus is point-and-call (PC) when a driver receives visual signals. However, PC does not reduce the subjective mental workload indicating it has no contribution to maintaining train driver energy level [3]. Actually, the ability to focus while performing a cognitive task is highly related to energy level. The train driver with lower energy levels due to fatigue tends to choose a risky driving strategy [4]. Consequently, the journey is not only less safe but also more costly due to the higher energy consumption. This study aims to construct a conceptual framework of cognitive workload management (CWM) based on cognitive energy expenditure (CEE) to ensure the train driver choosing the safe driving strategy throughout the journey.

Different from the technical factors, HF is hardly manageable through an ordered activity such as logging, timely check, and planned maintenance. The overall control of an HF's biological and psychological aspects is impossible. Current safety standard operational procedure (SOP) enforces a train driver to follow basic health checks and fatigue assessment before embarkation is allowed [5]. However, the SOP only accounts physiological factors and resides the train driver state of mind readiness to perform cognitive tasks. Meanwhile, HF consists of physiological and psychological factor. Moreover, cognitive task is not only a psychological task but also a physiological task. The indication of the cognitive task as a physiological task is the increase in thermogenesis of a worker in a sedentary workstation without involving physical activity [6]. Thermogenesis is a biological body heat generation process from basal metabolism (obligatory thermogenesis) or a response to physiological work (facultative thermogenesis) [7]. Accordingly, cognitive task induces facultative thermogenesis. Hence, tracking the energy expenditure of cognitive and physical workloads is critical to ensure overall safety.

Physiologically, the neuron action potential (NAP) can track the energy expenditure while someone performing a cognitive task. NAP or neuron membrane potential is an electrical impulse that passes the collection of information within an Axon from dendrites along the nerves [8]. The sensory perception of stimulation sends signals through synaptic terminals. The signal transmitter neuron terminal called presynaptic terminal while the receiving neuron terminal called postsynaptic. The resulting phenomenon is called a firing neuron which requires about +70 mv for depolarization. Depolarization is a process of shifting neuron membrane cell electrochemical gradient from a resting membrane potential (RMB) of –70 mV to pass 0 mV. The constant activation from the presynaptic neurons gradually depolarizes postsynaptic neuron. As a result, hyperpolarization may occur as the electrochemical gradient of the postsynaptic neuron exceeds 30mV and fallback to below the RMB [9]. The input signals trigger depolarization and are regulated by voltage-gate and mechanic-gate protein ion channels with a proton pump to control extracellular and intracellular ion exchange. A requirement to operate the pump is the energy in the form of Adenosine triphosphate (ATP). The ion-exchange is a homeostasis mechanism to maintain neuron cell balance [10]. Therefore, the energy expenditure pathway of cognition is through the ion pumps switching mechanism.

Besides the cognition energy expenditure (CEE), the condition of cognitive underload and overload affects train driver performance. The Train driver task classification study using multi-resource model framework classifies train driver cognition during the operation [11]. The results show a train driver may perform multiple cognition processes including spatial, auditory, and verbal at the same time and immediately switch to motoric task. Meanwhile during long distance journey, a train driver is more likely to idle while maintaining speed. Hence, a train driver is prone to cognitive overload and underload. Cognitive overload overwhelms the train driver which increases the probability of cognition error [12]. On the other hand, cognitive underload is a condition where the train driver only performs simple tasks with few or no repetition [13]. The train driver workload study of on-train-data-recorder (OTDR) shows the use of OTDR to directly evaluate the task performance of a train driver [14]. Instead of evaluating performance, this study use OTDR data to calculate workload of a train driver as the basis to determine next duty readiness.

Train driver's CW is one of the driving strategy quality indicators. Functional near-infrared spectroscopy (fNIRS) measurement of train drivers' cerebral oxygenic blood flow (oxy-Hb) reveals manual train operation increases prefrontal cortex activity compare to automatic train operation [15]. The more sophisticated model uses machine learning (ML) to identify a train driver's cognitive state according to a biophysical marker such as an EEG or Electrooculography (EOG). The less intrusive system with fastest ensemble ML algorithm allows the placement of EEG electrodes on forehead only [16]. However, the personal movement restriction still exists, making the system remain intrusive. This study proposes non-intrusive cognitive workload management (CWM) through neuronal dynamics approximation of train driver brain regional activity.

This study expands the [14] train driver cognitive task analysis from OTDR data by rating the synaptic energy usage during cognitive task performance. The task classification was according to the multi-resource model as previously done by [11]. As a result, this study proposes a cognitive energy tracking (CET) model to track cognitive auditory, spatial, and verbal task CEE. The implementation of the CET model in this study focuses on the train driver's CWM. The developed CET model can be a low cost and more practically applicable CWM as an alternative to more sophisticated EEG-based CWM developed by [16]. The CWM also support train driver readiness evaluation (DRE) system to evaluate duty readiness of a train driver based on the CET and driver mental condition.

2. Materials and Method

2. 1. Train driving operation data collection

The data to evaluate the CEE approximation model and cognitive load analysis was obtained from the secondary sources and simulation. The train driver operation secondary data was collected from the Virgin train on-train-data-recorder (OTDR) reported by [17]. The train driver actions record from the OTDR was listed. The observed tasks were control, signal sending and receiving, horns, gear shift, braking, close or open doors, cabin light switching, headlight switching, and communications. The cognitive workload was the number of the discrete performed tasks in a certain continuous time duration that measured as task (k) over time (min). This study evaluates the task in duration of 66 minutes.

2. 2. Brain region simulation

The brain region simulation was performed using The Virtual Brain (TVB) software version 2.4.1. TVB is brain white-matter track simulator software that simulates the neuronal dynamics phenomenon on brain cortical surface or regions [18]. The simulation in this study was run with 6000ms length using generic 2D oscillator model. The generic 2D oscillator is a simple oscillator harmonic oscillator model to simulate physical system [19]. TVB use the oscillator to simulate NAP state vector denoted with V and IMC state vector denoted with W. The oscillator parameter setup is shown in **Table 1**. The simulated brain connectivity was the TVB built in 76 region connectivity consists of the right and left hemisphere. The region covers some prefrontal cortex, some auditory, motor, visual, association areas, amygdala, and the full region list can be found in the TVB study [20]. The region stimulus signal was made using a pulse train function with onset of 10.0, fire period (T) of 100.0 ms, fire duration (tau) of 10.0 ms, and amplitude of 1.0. The maximum NAP of each region was set to maximum of 20 mV for excitatory regions and –65 mV for the inhibitory regions. The information about the excitatory and inhibitory regions was obtained from [21–25]. Therefore, the stimulus indicates a fully working brain which represents the point and call procedure.

2. 3. CWM framework testing and evaluation

The test and evaluation aim was to ensure the capability of the developed CWM framework to ensure the capability of the framework as the basis to train driver HF evaluation. The evaluation on the impact of cognitive load to energy level and motivation was performed. The test was by a train simulator testing followed by 27 participants. The participants were asked to play a Microsoft train simulator in 30 minutes coupled with Open rail V1.4 software to log the train driving activity data. The simulator journey was a single station passenger activity along Hisatsu Line, Kyushu Island, Japan in a clear weather condition using a Japanese diesel-hydraulic train KiHa 31 series. The tasks throughout the journey were not requiring significant attention and complex action. However, the events occurrences such as crossing animals and another train passing by were set random. Hence, the journey designation was to measure the participants' emotional adaptation in a cognitive underload situation. After playing the simulator, the participants were asked to fill a questionnaire regarding to their cognitive experience during the simulation journey (Appendix A). The test was open for experienced and inexperienced participant to measure the impact of task novelty and task structures. The test result is the basis to determine control limit and the task classification system for the CWM framework which applies to various cognitive job redesigns. The descriptive statistics summary of the questionnaire responses is provided in the. The variables at the head of the **Table 1** represent each question in the questionnaire. The participants' age was ranging from 20 to 42 years old with 4 respondents under 26 years old, 7 respondents in between 26–27 years old, 2 respondents 29 years old, and 12 respondents between 35–42 years old. The participants were predominantly male consists of 25 from 27 participants with only 2 females. The participants consists of 4 rail hobbyists, 19 with experience of playing train simulator, and 4 neither with experience of playing train simulator nor having rail knowledge.

Table 1

Descriptive statistics of the questionnaire response

–	Age	Gender	Experience	Overwhelmed	Bored	part_overwhelmed	minutes_overwhelmed	part_bored	ready_again	regular_duty_ready	mood_change
Valid	27	27	27	27	27	27	27	27	27	27	27
Missing	0	0	0	0	0	0	0	0	0	0	0
Mean	32.519	0.074	2.222	0.481	0.815	2.741	4.259	1.926	0.704	1.741	1.444
Std. Deviation	6.908	0.267	0.934	0.509	0.396	1.196	7.236	1.385	0.609	1.130	1.188
Minimum	20.000	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000
Maximum	42.000	1.000	4.000	1.000	1.000	6.000	30.000	5.000	2.000	4.000	4.000

The questionnaire responses and some ideal boundary conditions were used to design duty readiness evaluator (DRE). All DRE techniques were design and tested using JASP software. The variables types in the **Table 1** were rescaled from the nominal to scale and ordinal variables. The text questionnaire responses were converted to ordinal number by numbering each response in order from 0 to the last responses. The multiple responses (checkbox answers) were converted by adding each choice ordinal number. The target variables of the DRE were willingness to take similar cognitive load in daily basis (represented by regular_duty_ready variable) and readiness to continue the ongoing cognitive activity (represented by ready_again variable). Prior to DRE building, the average cognitive load of each participant was included in the dataset. Also, some ideal boundary conditions to direct the DRE model were added to the dataset. The ideal boundary was the condition during extreme underload, extreme overload, and normal load, which predicTable but does not understood by the model. The DRE implementation was using X-mR control chart, which built using JASP software for human-to-human assessment.

2. 4. Cognitive task energy formulation

The simulated signal consists of two state variables which is neuron action potential (NAP) denoted by V and IMC denoted by (W). W is an electrical current passing across the neuron cell membrane which equivalent to the number of charges noted as in equation (1), (2). The NAP in equation (3), (4) is the electrical voltage of brain signals across the post-synaptic terminal. Because the voltage represents the energy to move each charge (q) as denoted in equation (3), the number of charge at a time is modeled as in equation (5). The unit equivalency is denoted by the equation (6).

Let,

$$I=\frac{q}{t}(\mathrm{C/s}), \tag{1}$$

$$I=\widehat{W}(\mathrm{mC/s}), \tag{2}$$

and

$$V=\frac{E}{q}(\mathrm{J/C}), \tag{3}$$

$$V = \widehat{V}\left(\mathrm{mJ/mC}\right), \tag{4}$$

$$q = \widehat{W}t\left(\mathrm{mC}\right), \tag{5}$$

$$1\left(\mathrm{mJ/mC}\right) = 1\left(\mathrm{mV}\right). \tag{6}$$

In,

$$CTL = \frac{\sum Ch \times \widehat{V}}{\sum Ch}\left(\mathrm{mV}\right), \tag{7}$$

where

$$E = CTL \times q\left(\mathrm{mJ}\right). \tag{8}$$

CTL is the cognitive task load voltage derived from the average connectivity channel region denoted with Ch. The energy expense on each cognitive task calculated using equation (8) as the multiplication between average cognitive task load and the simulated brain signal charge. Hence, the equation (8) is the approximated CEE.

2. 5. Cognitive load determination from CEE

The cognitive overload and underload phenomenon only describable through discrete equation since the tasks were discrete. However, the tasks were performed in continuous time-space so that the energy expenditure is continuous as in equation (9). Therefore, the (9) transform to (10) through the application of Fourier series:

$$CL_{(t)} = \frac{dE}{dt}\left(\mathrm{mJ/s}\right). \tag{9}$$

Continuous time (t) discrete frequency (number tasks performed) conversion using Fourier series. The application of Fourier series in this study was through a scientific Python programming language package Scipy using the fft submodule. The Scipy fft equation is directly applied so the $k = -\infty,\cdots,+\infty$ at the discrete CL is as shown in equation (10):

$$CL_{(k)} = \int_{0}^{p} CL_{(t)} e^{-j\omega t} \mathrm{d}t\left(\mathrm{mJ/k}\right). \tag{10}$$

With is the number of performed tasks in the continuous time-space.

Since the wave properties of CL is the result of NAP evolution pattern, the generic 2D oscillator properties is applicable in transformation equation (10). The properties is adjusTable to another simulation equation models such as Kuramoto, Hopfield, Wong-Wang, Stefaniscu-Jirsa, or the real brainwave recording data such as electroenchepalography (EEG). The sigmoid function in equation (11) transforms the range of k to between 0 and 1:

$$Sig\left(CL_{(k)}\right) = \frac{1}{1+e^{x}}, \tag{11}$$

$$\lim_{dt\to 0}\left|CL_{(k)}\right| = 0, \tag{12}$$

$$\lim_{dt\to 0}\left|CL\left(k\right)\right| = 1. \tag{13}$$

The definition of Cognitive overload and underload situation can be depicted as the limit of k to the possible human cognition limit. This study assumes the possible maximum cognitive workload is 1 k/s and the minimum workload is 0 k/s. Therefore, the CEE of cognitive underload situation is mathematically defined as in equation (12) and Cognitive overload is mathematically defined as in equation (13).

3. Results and Discussion

3. 1. CEE from brain region simulation

The brain region simulation gives insight to regional activity of each brain channel of the chosen built in white matter track connectivity. The regional stimulus depicts neuron-firing phenomenon in a collective manner at regional level. Visually, the right-hemisphere visualization in **Fig. 1, *a*, *b*** shows the difference between inactive and active brain regions. The active regions with excitatory neuronal population shows brighter color image (**Fig. 1, *b***). Meanwhile, the inhibitory regions have indifferent color image. The color represents the NAP of each brain region or channel.

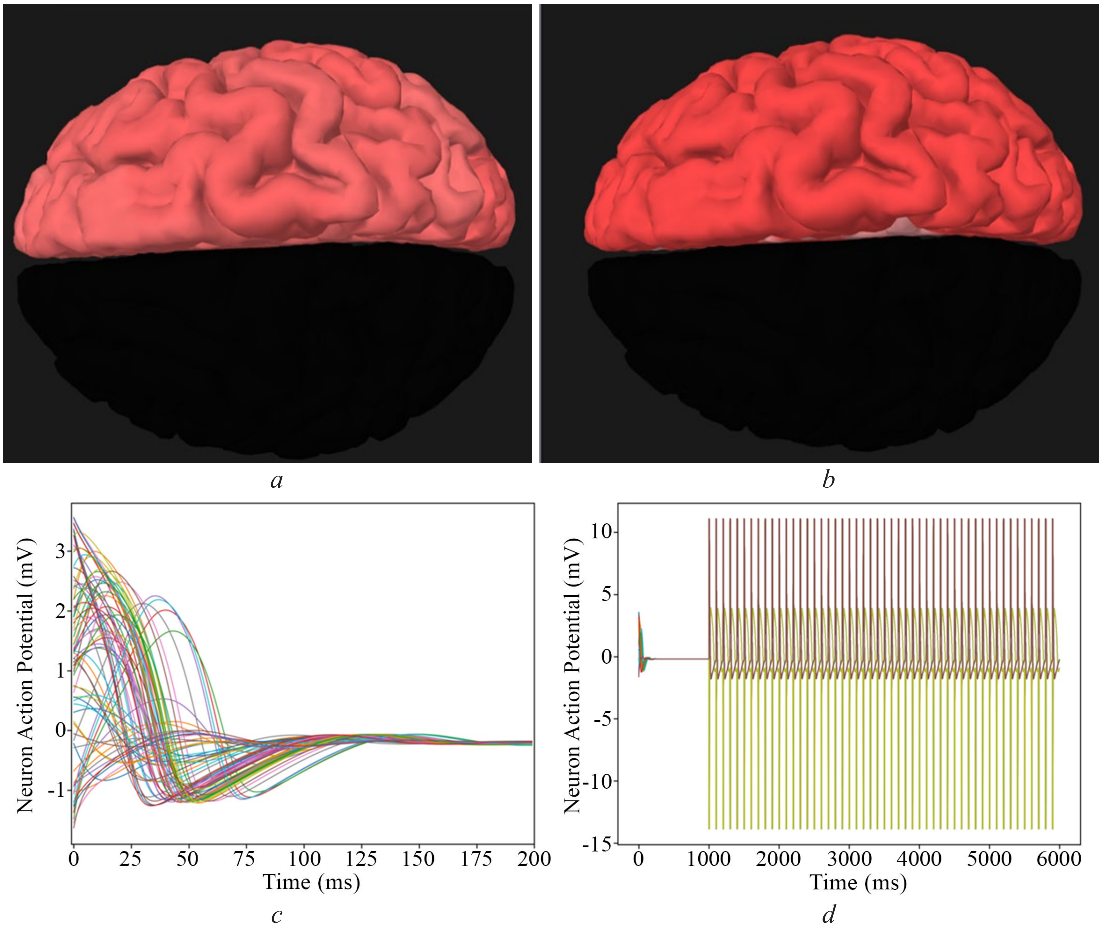


Fig. 1. The brain regional simulation results:
a – brain regions before activation; *b* – brain regions during activation; *c* – time series data shows random initialization of NAP at initial stage of the simulation;
d – time series NAP during activation

Alongside the visual representation of the regional neuron firing activity, the brain simulation also outputs time series version of the NAP. The time series data plot the activity of all 76 channels from the chosen connectivity as seen during the random initialization phase in **Fig. 1, *c*.** Random initialization is a neuron firing activity at the beginning of the simulation with duration of 200 ms and uncontrollable by TVB users. Proceed from 200 ms duration, all channels are inactive. The designed regional stimulus start at a duration of 1000 ms repeatedly until the simulation is over at a duration of 6000 ms. As shown in **Fig. 1, *d***, the time series NAP plot area above 0 mV indicates the activated region due to the stimulation. The plot area under 0mV indicates the inhibitory regions, which keep inactive. Accordingly, the simulation correctly represents the designed regional stimulus.

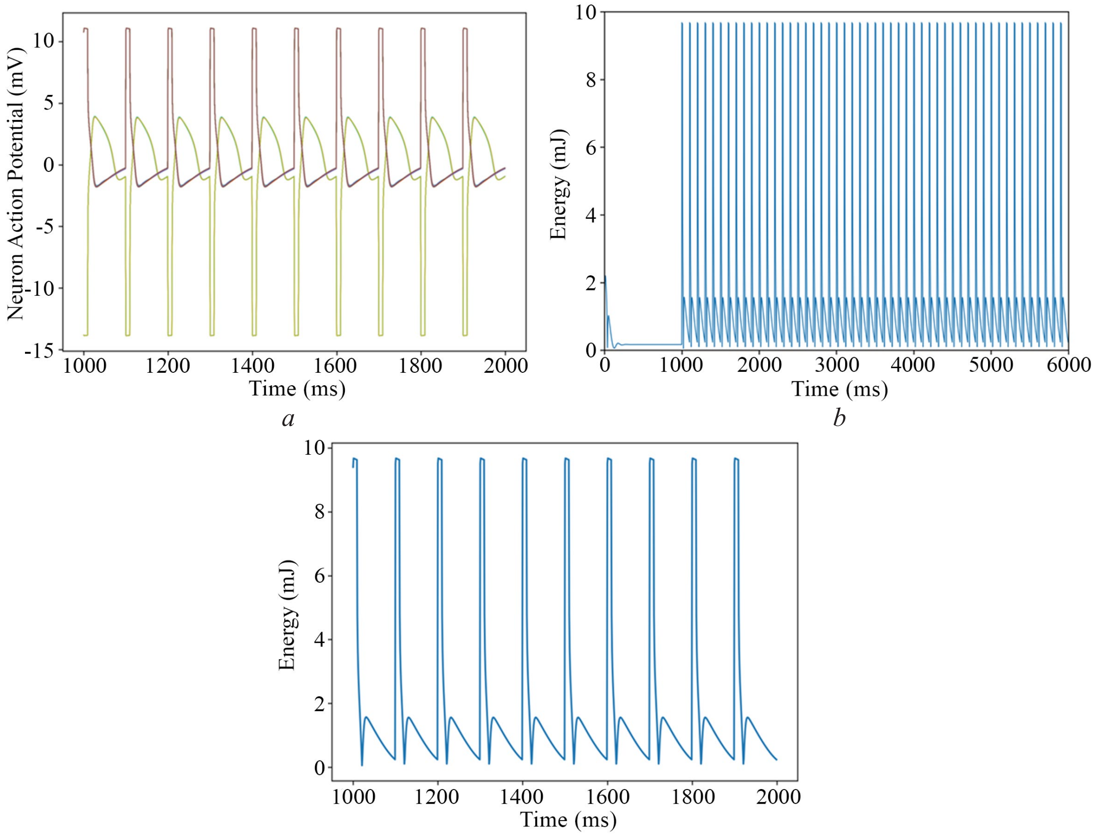
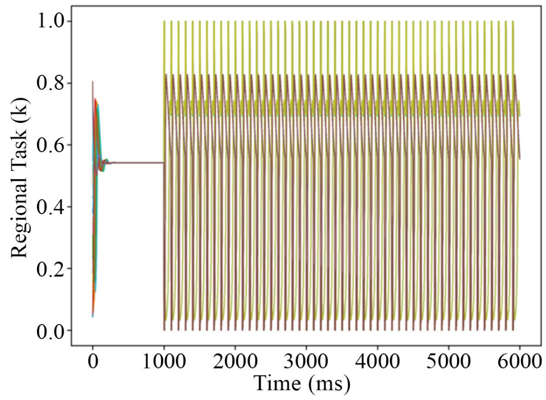


Fig. 2. Utilization of brain simulation results:
a – excitatory vs. inhibitory region NAP; *b* – total CEE of the tasks; *c* – CEE during activation

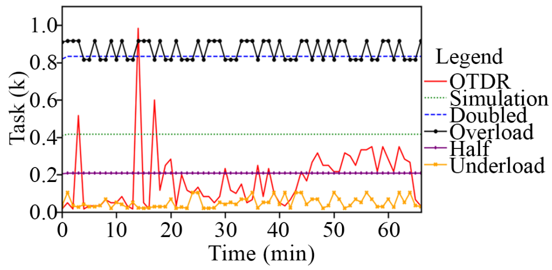
The CEE derived from the NAP and IMC state vectors as the output of the brain region simulation. The CTL as the average NAP due to cognitive task load (7) is consists of excitatory and inhibitory NAP with the example patterns as shown in **Fig. 2, *a***. Since most regions in the connectivity are excitatory, the CEE calculation using (8) give a positive result as shown in **Fig. 2, *b***. During the stimulation, the CEE is constantly from 0 mJ to 10 mJ as depicted in **Fig. 2, *c***. Hence, the predominant neuronal population response to the stimulus has more significant role to determine the CEE than the NAP value.

3. 2. Cognitive workload analysis

The comparison of cognitive workloads indicates the effect of certain cognitive load exposure. The OTDR data shows non-uniform pattern, which reveals that a train driver physical and cognitive task load is not exactly predictable. The task unpredictability of a train driver is due to the situation dynamics. Continuous perception to train control parameters and rail-traffic signs enforce a train driver to react according to the given situation. Meanwhile, the simulation data represents perception to the constant situation as in **Fig. 3, *a*** which gives the flat line plot in **Fig. 3, *b***. Regional task in **Fig. 3, *a*** is the task in each of 76 brain region channel. The half and doubled load were also created based on simulation load, which share same characteristic with different values. The overload and underload situation were randomly generated. The overload plot position on top of the doubled load indicates its CEE is more than twice the normal CEE. Frequent performance of high energy task is more likely to induce fatigue [1]. As oppose, the underload situation only require less than half normal CEE which also means a train driver has to perform easy task repetitively. Repetition of simple tasks in a long period causes boredom and prone to increase stress [2]. Boredom reduces the attention which also lower the alertness [3]. Therefore, the cognitive underload situation is simultaneously increases stress and reduces ride safety at some certain periods.



a



b

Fig. 3. Cognitive workload comparison:
a – cognitive workload of each brain region; *b* – comparison of train driver's cognitive workloads

The involvement of cognitive load to train driving work design is critical to improve train ride safety. Balancing cognitive load by taking the subjective and objective workload into the account is required. The subjective workload measures the level of overwhelms a person acquires by performing certain tasks [4]. The subjective workload takes the emotional factor into the account. Techniques such as National aeronautics and space Administration task load index (NASA-TLX) includes the performance level and frustration level evaluation which dependent to the current situation of a respondent. Therefore, a bias may present on the subjective workload evaluation results.

The combination of objective workload detection with subjective workload is an available solution to overcome bias in workload evaluation. This study makes use of CEE approximation as an approach to predict physiological cognitive workload which represents the objective workload of a train driver. Many sophisticate measurement technique that can be applied in real-time mental workload detection. However, most of those techniques are intrusive because the need of an additional equipment that restricts human movement. For example, the placement of EEG sensor on a train driver forehead hinders his/her ability to look outside the window when needed. Therefore, the work effectiveness of a person has to be sacrificed to use more sophisticate technology. Hence, the advancement in workload analysis technology does not reflect the correct principle of ergonomics. Despite the advancement in medical sensor technology, the objective cognitive workload measurement is still challenging due to the some physical factor that tied to the emotional factors. The example of it is the reduction in muscle strength when a person sad which indicates the information processing in mind determines the musculoskeletal work performance [26]. Therefore, this study provides non-intrusive cognitive workload analysis through OTDR data and also provides detail CEE approximation technique to prevent physical fatigue of a train driver.

3. 3. Framework evaluation

The results of the study are utilized as the basis to construct a DRE to manage train drivers' mental and physical condition. Prior to the construction, the viability of the OTDR and simulation data to predict the mood and the readiness of a person has to be tested. Hence, the questionnaire based train simulation test was performed. The participant with different level of background and experience level feels different level of boredom and overwhelms during the test. More participants with some experiences in playing train simulator feeling bored in the middle of the journey. Meanwhile, new train simulator players are more excited to play the simulator itself instead of focus on the route condition that affects the challenge level of the journey. The perception of novel task such as train simulator for the new players is more rewarding [5]. However, all of the participants pick the station stops and the embarkation as the most challenging task. The average cognitive load during that phases also the highest throughout the entire journey. Most of the participant also chooses to take one day rest if they have to repeat the same train driving task.

The duty readiness evaluation systems that embedded in the CWM is a human-to-human evaluation. The human-to-human evaluation performed by using the control chart that built based on the average cognitive load. **Fig. 4, *a*** shows a control chart for daily routine duty readiness. The subgroups in this control chart are the responses of participant willingness to perform 8 hours a day (40 hours/ week) daily train driving operation. The participants with average cognitive load in between 0.2 to 0.4 are mainly in subgroup 2, which are the participants than need more than one day break period. Subgroup 1 that represents the participants that need one day for break each week are having average cognitive load of 0.0 to 0.2 and 0.4 to 0.6. The participants in subgroup 3 that only willing to perform train driving operation in 4 hours/day are having average cognitive load under 0.2 and 0.8. Therefore, the average cognitive load of participants in subgroup 3 represents the cognitive underload and overload situation. Subgroup 2 represents the below average cognitive load and subgroup 1 for the average or normal cognitive load. The result indicates the participants with normal cognitive load require a single day break each week. The participants that experiences low cognitive load require more than one day break while participants with the underload and overload situation demands less train driving hour which is 4 hours/day.

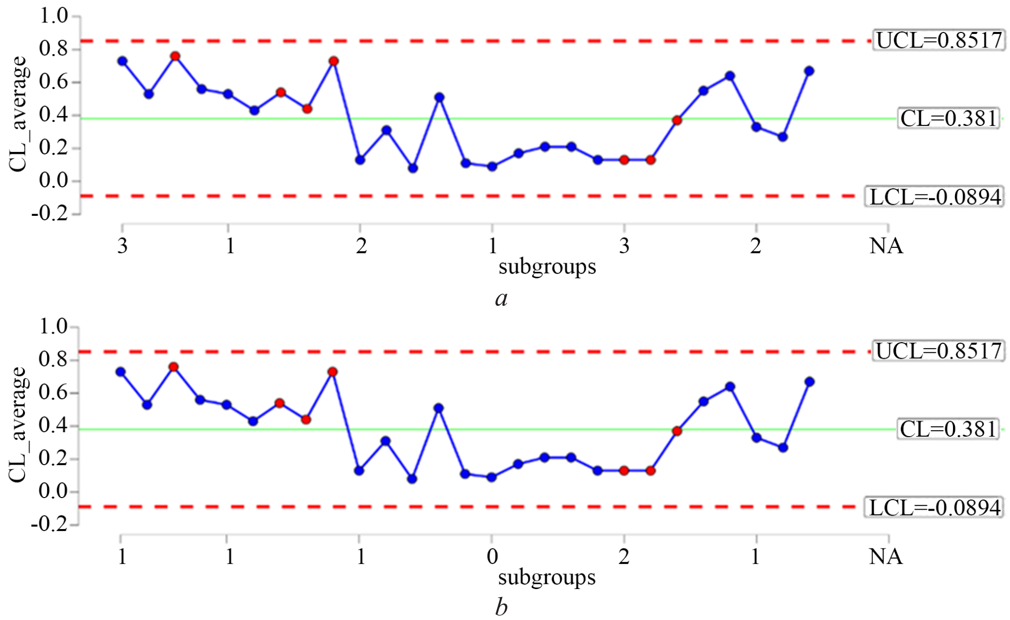


Fig. 4. Control charts for readiness evaluation:
a – routine or daily duty readiness; *b* – ongoing duty readiness

The ongoing duty evaluation also performed using the same control limit based on the average cognitive load. The ongoing duty readiness is the willingness of the participant to continue current train driving operation. **Fig. 4, *b*** shows the same control limits applied to different subgroups. The subgroups represent the participant responses of readiness to start another journey. Subgroup 0 represents «yes» answer, subgroup 1 represents «after some break» answer, and subgroup 2 represents «no» answer. The average cognitive load values that fall into subgroup 0 are cognitive underload value from 0.0 to 0.2. Subgroup 2 only consists of underload values under 0.2 and subgroup 1 represents normal and cognitive overload values. Hence, the interpretation of the ongoing duty readiness evaluation is the participants with normal workload and high workload both need break and rest period during duty.

The average cognitive load defines different expected treatments for the train drivers based on their workload experience throughout the journey. Therefore, the division of each treatment according to the provided subgroups helps the management to fit the needs of the train drivers to refresh their mental state. Defining weekly rest period and short daily rest period as expected by the train driver will maintain each train driver normal performance. As a result, the train driver always chooses the best driving strategy, which is the safest, and the most effective strategy. Also, the probability of human error is reduced in a good mental condition [6]. Therefore, the train parameter control according to the rail-traffic sign and situational perception are ensured mostly correct or under the specified threshold. Cognitive load value as an indicator of CEE also represents the energy level of a train driver that can be linked to the physical fatigue. Thus, the human-to-human CWM framework maintains train driver physical and mental condition to keep them ready in their best performance for each train driving duty.

3. 4. Whole design of the framework

The construction of the CWM framework is based on CEE derived average cognitive workload and questionnaire based subjective workload. Both results used for DRE as the main part of the CWM. Hence, the CWM can provide different feedback according to the given train driver condition. **Fig. 5** shows the architecture of the CWM framework with the circles are the entities involved, the squares are the data transformation flow, the ovals are the output variables of the CWM framework, the parallelogram is the output variable processing as the decision support, and the arrows are the relational process. The flow starts from the train driver operating the train, which outputs OTDR data. The OTDR data copied to the management and then processed further to obtain cognitive load value. The average cognitive load value then calculated which outputs CEE. The average cognitive load is used as in readiness evaluation to support management decision in treating each train driver based on their workload. The conditional control through the application of control chart provides the suggested decision for the management. Hence, the management can determine daily short rest period and weekly rest period, which affect the train driver scheduling.

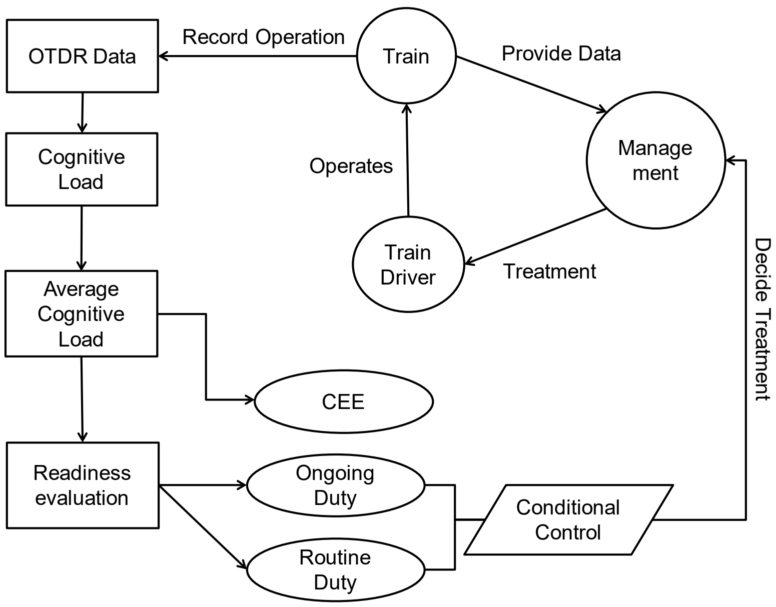


Fig. 5. The CWM framework architecture

The CWM framework provided as an alternative technique that can be quickly implemented among other train driver CEE tracking and DRE. The tradeoff of the CWM framework with more sophisticated techniques is provided in **Table 2**. The CWM framework does not provide real-time CEE measurement that restricts the movements of a train driver. The CWM framework implementation also does not require locomotive or train control technology upgrade. The output of CWM framework is comparable with a sophisticated ensemble learning method developed by [16]. Different from the computational based evaluation technique using expert system as developed by [27–29] and using support vector machine (SVM) by [30], this study apply human-to-human evaluation which involve emotional factor of a person. The CEE approximation method that proposed in this study also constructed based on simulation data. As a result, the noise that may occur in the real world is not taken into the account by the model. However, it is clear that the CWM framework can be an alternative technique or a backup technique for the sophisticated technique that rely on computational method.

Table 2
Comparison of CWM framework with real-time evaluation techniques

Study	Evaluation Technique	Output	Device	CEE Approximation	Intrusive	Movement Restriction	Technology Upgrade
This study	Control Chart	Decision Support	OTDR	76 Brain Region Simulation	×	×	Not needed
[16]	Ensemble Learning	Decision Support	EEG	Frontal EEG	×	✓	Needed
[29]	Expert System	Fatigue Potential	EEG	Frontal & Temporal EEG	✓	✓	Needed
[30]	Support Vector Machine	Vigilance level	EEG	8-channel EEG	×	✓	Needed

The CWM framework that has been developed in this study has some limitations and room for improvements to increase the effectiveness of the model in the future. The CEE tracking in CWM framework was built upon neurodynamics simulation principle. As a consequence, the empirical factor is not present in the model. Therefore, further analysis in the CEE approximation technique is required to include the empirical factor. The use of OTDR data also require data extraction process after every journey which tedious for the management. Therefore, the development of a technique or a device to safely capture OTDR data in real-time should be considered in the future. The use of machine learning based classification technique such as artificial neural network (ANN) or SVM to classify the subgroups in the control chart is also required to improve the management efficiency and reduce the emotional decision making that may present in human-to-human evaluation.

4. Conclusions

The main result of this study is the cognitive workload management framework for driver readiness evaluation to provide correct treatment for each train driver according to their workload. The framework has a dual function as a physical fatigue and stress prevention system. Both physical and stress prevention correlates to the driving strategy decision making and driving performance of a train driver. This study also outputs the cognitive energy expenditure approximation technique that tested with brain region simulation as the physical cognitive workload estimator. The framework application is human-to-human using the control chart to groups each train driver average cognitive load to the demanded treatment during ongoing train driving duty and routine daily train driving operation. Each subgroup represents the required break duration for each participant with 0.0 to 0.2 one day break each week and 0.4 to 0.6 cognitive load requires shorter regular break. The participants in subgroup 3 that only willing to perform train driving operation in 4 hours/day are having average cognitive load under 0.2 and 0.8. The participants in subgroup 3 that only willing to perform train driving operation in 4 hours/day are having average cognitive load under 0.2 and 0.8. The average cognitive load from the OTDR data determines the corresponding train driver subgroup in the control chart. Therefore, each train driver recovery time and recovery technique can be determined objectively. Thus, the cognitive energy expenditure derived average cognitive load value is useful to provide decision support for the railway human factor management to treat each train driver in different way.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data availability

Data will be made available on reasonable request.

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