Proceedings of the 33rd European Safety and Reliability Conference (ESREL 2023)
Edited by Mário P. Brito, Terje Aven, Piero Baraldi, Marko Čepin and Enrico Zio

doi: 10.3850/978-981-18-8071-1_P712-cd

Investigating the Impact of Day-Night Conditions and Time Progression on the Fatigue of Maritime Autonomous Surface Ship Remote Operators: Implications for Remote Control Centre Design

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Maritime Autonomous Surface Ships (MASS) have attracted significant interest in recent years due to their potential to confer economic, safety, and environmental benefits. However, a key aspect of the MASS system that remains unclear is the scientific and reasonable design of Remote Control Centers (RCCs), which is responsible for remotely controlling and monitoring MASS operations. RCC design can significantly impact the performance of remote operators. Therefore, this study aims to investigate the impact of day-night conditions and time progression on the workload and fatigue level of MASS remote operators, in order to provide guidelines for RCC design. A remote-control simulation platform was utilised to conduct two rounds of 4-hour daytime and night-time remote control experiments. Physiological data were collected in real-time using various measurement instruments, and the Karolinska Sleepiness Scale (KSS), Reaction time (RT), and NASA Task Load Index (NASA-TLX) were assessed every 25 minutes. Some findings suggest that fatigue level in the night-time condition is higher than in the daytime condition, sleepiness significantly increased over time and reached a peak at around 1.5 hours (daytime) and 2 hours (night-time), before maintaining a steady level, which means day-night conditions and time progression can significantly impact remote control operators' performance potentially leading to decreased performance and increased risk of misoperation. The study highlights the need for effective work schedules and interventions to improve remote control operators' performance in MASS operations. This research takes the first step to the investigation of the remote control centre operator, and could provide valuable insights into the design of RCCs, which will improve the performance of RCC operations and ensure the safety of MASSs.

Keywords: Maritime Autonomous Surface Ships, Remote Control Centers, Fatigue, Shift Configuration.

1. Introduction

In recent years, remote work has gained popularity, with many companies allowing their employees to work from home or other remote locations. However, remote work is not limited to traditional office settings. With the advent of Maritime Autonomous Surface Ships (MASS), remote control of ships is becoming a reality. MASS are ships that operate without a crew onboard, controlled remotely by human operators located onshore or by artificial intelligence systems. Remote control of MASS has several advantages, such as increased safety, cost savings, and reduced carbon emissions (Fraunhofer, 2016; Lindstad et al., 2015; Ramos et al., 2019).

Numerous studies have investigated the design and implementation of MASS, focusing on various aspects such as navigation and control systems, communication, and collision avoidance. For example, Zhang et al. (2021) proposed a real-time collision avoidance framework for MASS using B-spline and optimal decoupling control. Guan et al. (2022) introduced a novel offshore communication structure by deploying Unmanned Aerial Vehicle (UAV) mounted relay nodes between RCC and MASS and proposed an optimised algorithm to adapt off-shore communication situations. Despite these efforts, several challenges must be addressed before MASS can be widely adopted, particularly concerning the remote control centres (RCC).

The adoption of MASS poses significant challenges, particularly in terms of the changing roles and responsibilities of the crew. The traditional roles of the crew, such as navigation and ship-handling, have evolved into more complex tasks, such as monitoring and decision-making, requiring a higher level of cognitive skills and knowledge. As such, investigating the human factors involved in MASS navigation, including the crew's workload, performance, and well-being, is essential to ensure safe and efficient operation (Man et al., 2015, 2018; Stephenson et al., 2021; Alsos et al., 2022).

Mental workload is one of the most important terms in understanding human performance. It is related to task demand, mental effort, and performance. Appropriate mental workload enables an operator to perform effectively and efficiently, while abnormal mental workload may lead to fatigue and even human-induced faults, which could eventually lead to an accident (Young et al., 2015).

There are many approaches assessing fatigue and mental workload, which can be broadly categorized into two main types: objective and subjective methods. Objective methods involve the measurement of physiological signals, such as heart rate variability, electrodermal activity, and reaction time, to provide an indication of fatigue and mental workload (Charles & Nixon, 2019). The Psychomotor Vigilance Task (PVT) is an example of an objective method that measures reaction time (RT) to visual stimuli. Wearable devices that monitor physiological signals are another objective approach, such as heart rate monitors and electroencephalogram (EEG) headsets (Marchand et al., 2021). Subjective methods involve the use of self-report measures, such as questionnaires or rating scales, to assess an individual's perception of their own fatigue or mental workload. Examples of subjective measures include the Samn-Perelli fatigue scale and the Karolinska Sleepiness Scale (Longo, 2017). Both objective and subjective methods have their strengths and limitations and can be used in combination to provide a more comprehensive assessment of fatigue and mental workload. Objective methods provide an accurate and reliable measure of physiological changes associated with fatigue, while subjective methods allow individuals to provide insight into their own perceived level of fatigue or mental workload (Kerkamm et al., 2022) (Hancock et al., 2021).

One area of confusion in existing studies on MASS is the operating mode under 24-hour full-day operation and the shift configuration of RCC. The RCC is a crucial component of MASS, and its mode of operation needs to be optimised to ensure the efficient and safe operation of the vessel. It is unclear how various factors, such as day-night conditions and time progression, influence the workload and fatigue levels of MASS remote operators. Furthermore, it is uncertain whether an operator's time on task should be limited due to these factors. This study aims to address this gap in knowledge and propose a shift design that can minimise potential safety issues caused by fatigue and abnormal workloads, ensuring the safe and efficient operation of MASS.

In this study, the methodology employed was introduced in section 2, which includes participant selection, equipment information, experimental procedures, and data acquisition and analysis. Section 3 provided the details about the final experiment data and results. In section 4, the implicit knowledge obtained from the acquired results was discussed and unfolded. Finally, the conclusion was summarised, and further directions were proposed.

2. Method

In this study, a simulated remote navigation experiment was performed to measure the operators' fatigue level and mental workload.

2.1. *Experimental setup*

Each experiment required one operator, one experimental testbed, and objective and subjective value measure equipment. When participants experiment, they should wear a customised wristband. During the experiment, they should complete several test batteries (the detail can be found in section 2.3). The equipment used during the experiment is listed below.

The testbed (see Fig.1) enables the 3D visualisation simulation of the navigation process of MASS. It can simulate the real-scale information of ships, dynamic sea condition environments, and navigation information perception. The testbed also offers various encounter scenarios and working conditions and supports research into MASS's track tracking, route optimisation, and collision avoidance algorithms.

Fig.1. Remote control simulator

The subjective method is composed of two scales, the NASA Task Load Index (NASA-TLX) and The Karolinska Sleepiness Scale (KSS). The NASA-TLX is a subjective assessment tool that measures perceived workload and mental demands. It was developed by NASA in the 1980s to evaluate the workload of pilots and astronauts. The NASA-TLX consists of six subscales, and respondents rate each subscale on a 0-10 scale, with higher scores indicating a greater perceived workload. It is widely used for assessing workload in various industries and domains, including human factors research and usability testing (Hart, S. G., & Staveland, L. E., 1988). In addition, the KSS is a subjective measure of sleepiness and alertness. It was developed at the Karolinska Institute in Sweden as a simple and quick tool for assessing sleepiness in research and clinical settings. The KSS consists of a 9-point Likert scale, with higher scores indicating greater sleepiness. It has been used extensively in sleep research and has also been applied in various industries to evaluate the impact of sleepiness on performance and safety (Åkerstedt, T., & Gillberg, M., 1990).

Regarding objective measurement equipment, this study adopted the physiologic signal acquisition customised designed wristbands (Ergosensing, China) (see Fig. 2), and further details can be found in the work by Zhang et al. (2021). In this device, the galvanic skin response (GSR) signal was acquired by surface electrodes with conduct gels at a sampling rate of 40Hz with a resolution of 0.01μS. photoplethysmography (PPG) was measured at a sampling rate of 20Hz with the reflected green light of 532 nm wavelength. PPG and GSR are two non-invasive physiological signals that can be used to measure HR and HRV. PPG measures blood volume changes, while GSR measures skin conductance related to sympathetic nervous system activity. The use of PPG and GSR to measure HR and HRV has gained popularity due to their ease of use and non-invasive nature.

Fig.2. Physiologic signal acquisition device

Besides, we tested the RT of participants with customised software which could deliver a visual and auditory stimulus.

2.2. *Experiment procedure*

The experimental procedure was inspired by the recent work of Glaros et al. (2021) and Li et al. (2022). Participants completed two 4-hour simulation navigation in randomised order, one beginning in the morning and another at night. Six participants had their two simulations on different days to ensure their best work conditions.

Participants were recruited openly, and before the commencement of the experiment, they were provided with a detailed explanation of the simulation's purpose and navigation plan. Participants were also informed that they could withdraw from the experiment at any time. Caffeine intake was recorded for all participants, including the type and timing of consumption before the experiment. At the beginning of the experiment, a baseline cognitive test battery was administered to participants, repeated every 25 minutes throughout the experiment. Eight test batteries (excluding the baseline assessment) were administered to participants until the completion of the navigation plan. During each test battery, participants were relocated to an isolated meeting room to minimise distractions while a designated mentor monitored the experiment and provided any necessary assistance. The whole procedure timeline is shown as below Table 1.

Table 1. Experiment procedure timeline.

Stage	Baseline test	Stage 1	Test 1	Stage 2	Test 2
Daytime	7:55-8:00	8:00-8:25	8:25-8:30	8:30-8:55	8:55-9:00
Nighttime	18:55-19:00	19:00-19:25	19:25-19:30	19:30-19:55	19:55-20:00
Stage		Stage 3	Test 3	Stage 4	Test 4
Daytime		9:00-9:25	9:25-9:30	9:30-9:55	9:55-10:00
Nighttime		20:00-20:25	20:25-20:30	20:30-20:55	20:55-21:00
Stage		Stage 5	Test 5	Stage 6	Test 6
Daytime		10:00-10:25	10:25-10:30	10:30-10:55	10:55-11:00
Nighttime		21:00-21:25	21:25-21:30	21:30-21:55	21:55-22:00
Stage		Stage 7	Test 7	Stage 8	Test 8
Daytime		11:00-11:25	11:25-11:30	11:30-11:55	11:55-12:00
Nighttime		22:00-22:25	22:25-22:30	22:30-22:55	22:55-23:00

Participants were asked to complete NASA-TLX, KSS, and RT tests when performing the test battery. At first, participants rated their sleepiness level using KSS, a nine-point Likert scale ranging from 1 = extremely alert to 9 = fighting sleep. Secondly, participants rated their workload on a NASA-TLX, a multidimensional scale designed to obtain estimates of the workload from operators. Participants completed a baseline assessment of workload prior to both simulation sessions to create individual weighted ratings. This consisted of a 15-item comparison in which participants were asked to compare which workload characteristics were more demanding. Each workload domain (i.e., Mental, Physical, and Temporal demands, and Frustration, Effort, and Performance) was weighted against an individual's perceived ratings. Finally, participants need to complete a RT test. The software comprises three reaction time tests: a simple RT test, a selective RT test, and an auditory RT test. In the experiment, the participants were administered the tests in the same order. For each round, the simple response test and the auditory response test stimuli were presented five times, while the selected response test stimuli were presented 10 times at random. The software would record the information of each participant and the corresponding experimental results.

2.3. *Data analysis*

In contrast to the experiment equipment, the acquired data could be divided into two parts:

- Subjective data: including NASA -TLX and KSS scale.
- Objective data: RT record and ECG characteristics such as RMSDD, SDNN, and IBI.

This study aimed to investigate the impact of two key factors – time progressing and day-night condition on the fatigue and workload experienced by remote control operators. To achieve this objective, we conducted two distinct data analyses.

On the one hand, we performed an ANOVA on RT data to observe the difference between day and night conditions, including simple RT data, selective RT data, and auditory RT data. In addition, we calculated the weighted average for each participant's NASA-TLX ratings and compared the differences between the daytime and nighttime simulations. We also processed the KSS scale results. Random effects for all samples were considered in this study. All calculations were conducted using SPSS 26 on a Windows 11 Pro (22H2) operating system.

On the other hand, the physiological signal acquisition device can produce several filtered characteristics of heart rate (HR) and heart rate variability (HRV), such as the interval between intervals (IBI), the standard deviation of successive inter-beat intervals (SDNN), and root mean square difference of successive inter-beat intervals (RMSSD). This study analysed the relevance of all pertinent characteristics with the day-night condition and cognitive performance changing over time.

3. Case study

3.1. *Participants*

Ten individuals were trained to operate a remote control navigation simulation, and all were subsequently invited to participate in the data collection phase. Since facing challenges in recruiting female volunteers for the full-day simulation, informed consent was obtained from six male volunteers who met the inclusion criteria. All participants were postgraduates of the navigation profession at the authors' institution, with a mean age of 24.8 (±2.28). Each participant self-reported having normal colour vision and hearing function. Additionally, all participants had a sufficient level of knowledge in navigation, given that they had a background in navigation studies.

3.2. *Navigation task*

Participants were responsible for remote controlling and managing a 4-hour sustain navigation under a day (8:00-12:00) and night (19:00-23:00) conditions. The navigation plan was bonded with realistic conditions: departure, straight-line sailing, encountering with another ship, obstacle avoidance, and arrival. Weather changes are also incorporated to ensure realistic conditions. Besides, the simulation environment was set on the Shenzhen Yantian Port, which ranks fourth globally regarding container throughput by 2022.

The four-hour navigation plan entails the operation and management of a 3000TEU container ship (TEU is a measure used in shipping to denote the cargo-carrying capacity of a container ship, equivalent to 3000 twenty-foot-long containers or their equivalent volume). During the simulation, participants observe a 3D model of Shenzhen Yantian Port and the sea, expecting to ensure the ship's safety. Specifically, participants must depart from the port and sail along the coastline for two hours, followed by a return trip to the port in the remaining two hours. Throughout the exercise, participants are exposed to several events every thirty minutes, including encountering another ship, avoiding a beacon, and weather changes from sunny to drizzly or drizzle to heavy rainfall, among others. Judged by the weather condition and required operation content, the task complexity is rated as arrival (stage 8), departure (stage 1), straight-line sailing under thunderstorm (stage 4), straight-line sailing on heavy rainfall (stage 3 and 5), and straight-line sailing under drizzle (stage 2 and 6 and 7).

The test navigation plan route with weather conditions can be found in Fig 3, and all the participants were informed to follow the navigation plan.

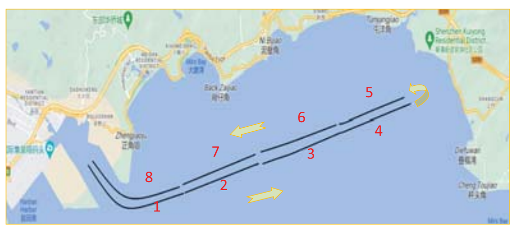

Fig.3. Navigation plan in the simulation

4. Results

4.1. *Scale and RT data*

4.1.1. *Scale and RT data with day-night condition*

Before analysing the retrieved data, the outlier data other than 3 times the standard deviation was removed. The ANOVA results showed significant differences between the daytime and nighttime conditions for NASA-TLX score(p＜

0.05). The night condition (M=43.85, SD=10.50) is significant higher than the day condition (M=35.90, SD=6.08). Participants rated their KSS score as significantly sleepier during the night simulation (M = 4.72, SD = 1.84), compared to the day simulation (M = 2.88, SD =1.83, $p < 0.001$).

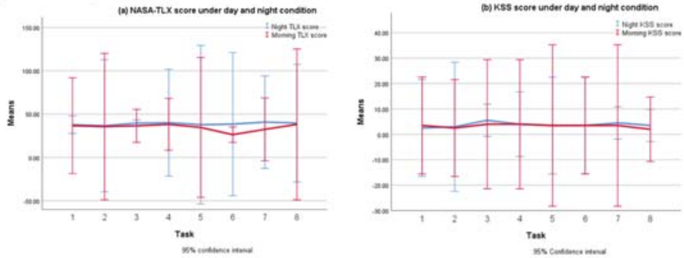

Fig.4. NASA-TLX (a) and KSS (b) scale result by task number. Error bars represent standard deviation

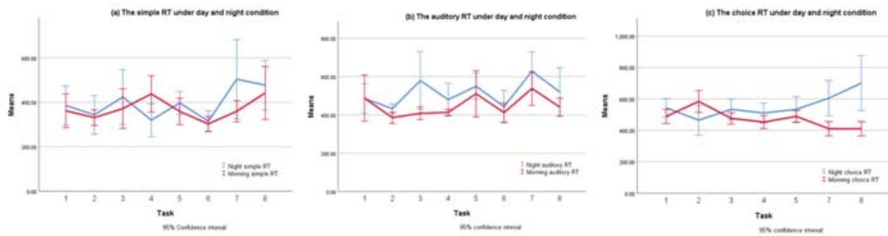

Fig.5. The simple (a), auditory (b), and choice (c) RT result by task number. Error bars represent standard deviation

The ANOVA results showed that there were no significant differences between the simple RT in day and night condition ($p > 0.05$). However, the auditory RT appeared an significant difference between day-night condition ($p < 0.05$). The night condition (M=536.34, SD=158.35) is significantly higher than the day condition (M=474.63, SD=129.41). Besides, the choice RT was also reflect an significant difference ($p < 0.05$). The night condition (M=533.27, SD=149.38) is significantly higher than the day condition (M=489.13, SD=100.26).

4.1.2. *Scale and RT data with time progressing*

The plotted data reveal several trends. Firstly, workload and did not significantly increase or decrease with time progressing during either simulation. Secondly, Sleepiness (KSS score) significantly increased over time and reach the peak at task 3 (around 1.5h), and then maintained a steady level. Thirdly, mean auditory RT significantly increased over time during the night simulation, while the day simulation reflected a decrease trend.

4.2. *Physiological data*

4.2.1. *Physiological data with day-night condition*

The extracted IBI, SDNN, HR, and RMSDD data were grouped into daytime and nighttime. Descriptive statistics for each group are presented in Table 2, including the number of data, minimum value, maximum value, mean, and standard deviation.

Table 2. Description statistics of characteristics.

Data	N	Min	Max	Mean	Std
IBI_M	195	540.41	880.78	784.97	41.93
IBI_N	188	613.44	855.65	746.45	53.26
HR_M	195	68.30	112.25	77.06	4.90
HR_N	188	70.41	98.33	81.12	5.96
SDNN_M	195	26.93	91.19	52.98	9.72
SDNN_N	188	20.77	76.90	45.76	12.03
RMSSD_M	195	15.83	69.49	41.91	9.13
RMSSD_N	188	19.23	70.82	40.362	10.36

To test whether there were statistically significant differences in each feature between the daytime and nighttime groups, homogeneity of variance and normality were first checked. If the data met the normality assumption, ANOVA was performed.

Four sets of P-P plots were generated using SPSS, as shown in Fig 6. All P-P plots showed approximately diagonal lines, indicating normality of the data.

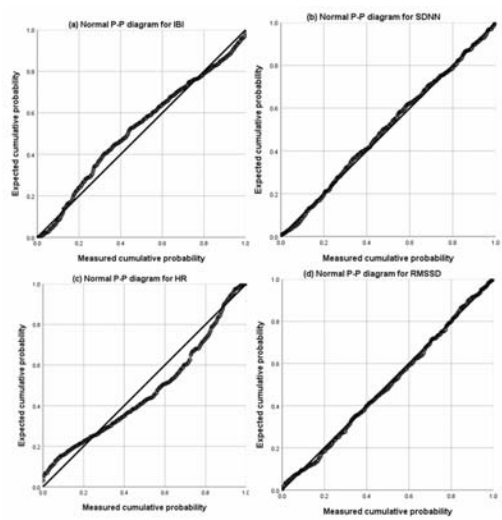

Fig.6. P-P plots of IBI (a), SDNN (b), HR (c), and RMSSD (d)

The ANOVA results showed significant differences between the daytime and nighttime conditions for IBI ($P < 0.001$), SDNN ($P < 0.001$), and HR ($P < 0.001$), but not for RMSSD ($P > 0.05$). As shown in Table 1, the values of IBI and HR values were significantly higher during the daytime compared to nighttime, while SDNN values were significantly higher during the daytime than at nighttime.

4.2.2. *Physiological data with time progressing*

According to the experimental design, each 4-hour session comprised 8 stages of varying task difficulty. This study produced graphs of the temporal changes in IBI, SDNN, RMSSD, and HR with respect to the diurnal cycle.

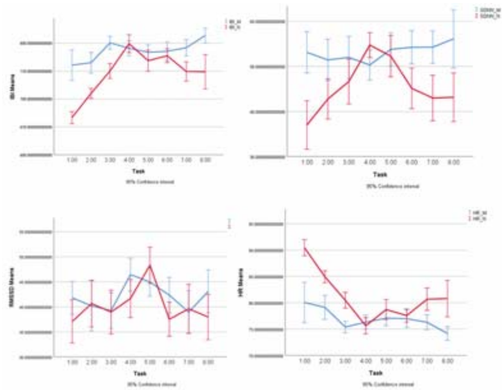

Fig.7. The IBI (a), SDNN (b), HR (c), and RMSSD (d) means by task number. Error bars represent standard deviation

As is shown in Fig 7, the plotted data reveal several trends. Firstly, the daytime IBI values were generally greater than those at night, and both followed a similar pattern of initial increase followed by a gradual decrease towards stabilisation. The maximum value for daytime IBI was observed at around 1.5 hours, while the peak for nighttime IBI occurred at approximately 2 hours. Secondly, the SDNN trend was completely opposite between night and day, displaying a slow decline followed by a rise during daytime, and a sharp increase followed by a decline during nighttime. Thirdly, there was no significant difference between daytime and nighttime RMSSD values. Lastly, the nighttime HR values were generally higher than their daytime counterparts. Both displayed a pattern of initial decrease followed by a return to a stable level, with the nighttime decrease being more pronounced.

5. Discussion

5.1. *Scale and RT data*

According to the Scale and RT data, the study found that workload did not significantly increase or decrease with time during either simulation, but sleepiness significantly increased over time and reached a peak at around 1.5 hours, before maintaining a steady level. The study also found that the auditory RT and choice RT were significantly higher during the night condition, indicating that participants took longer to respond to auditory stimuli and make decisions during this condition. The findings suggest that remote control operators may experience higher workload and sleepiness during night conditions, which could impact their performance.

The study highlights the importance of monitoring and managing operator fatigue to ensure safe and effective remote control operations. Besides, further analysis is necessary to uncover the underlying causes behind the observed trends, which can provide insights into how to mitigate the negative effects of remote operation in day-night conditions over time.

5.2. *Physiological data*

Regarding Physiological data, the study found that several factors may contribute to the observed trends in HRV during daytime and nighttime work shifts.

i. The higher daytime IBI values compared to nighttime may be influenced by the circadian rhythm and the parasympathetic nervous system's increased activity during the day. The pattern of initial increase followed by gradual decrease towards stabilisation may be due to the effects of workload on the autonomic nervous system. Besides, the peak in daytime IBI at approximately 1.5 hours and nighttime IBI at around 2 hours may be due to the variations in autonomic nervous system activity and hormonal secretion that follow a circadian pattern (Reyes et al., 2013, Buchheit, M, 2014, Koenig et al., 2014).

ii. The opposite trends in SDNN between night and day may be due to the effects of the sleep-wake cycle on the autonomic nervous system, with a slow decline and rise during the day reflecting increased parasympathetic activity and the sharp increase and decline during the night reflecting sympathetic activation (Chouchou and Romanella, 2014). Additionally, environmental factors such as light exposure, noise, and temperature may also influence HRV and contribute to the observed trend (Schnell et al., 2013).

ii. The lack of significant difference in RMSSD values between daytime and nighttime may suggest that this measure is not sensitive to circadian variations or workload demands and may be more reflective of overall parasympathetic activity.

iv. The observed higher nighttime heart rate (HR) values and more pronounced nighttime decrease could potentially reflect the effects of sleep and changes in sympathetic activity during different stages of sleep (Burgess et al., 1997).

Remote control operators of MASS could benefit from these findings by being made aware of the potential impact of their workload and circadian rhythms on their heart rate variability. Operators could take measures to reduce their workload during peak workload periods, such as taking short breaks or rotating tasks, to help maintain stable HRV levels. The observed trends in HRV during nighttime work shifts could also have implications for the scheduling of remote control operators. Operators may be more effective and efficient during periods of higher HRV, such as during the daytime, and may benefit from more rest and recovery time during periods of lower HRV, such as during the nighttime. The lack of significant difference in RMSSD values between daytime and nighttime suggests that this measure may not be sensitive to workload demands or circadian variations. This finding could have implications for the selection of HRV measures used to monitor and assess the health and performance of remote control operators, and may suggest that other measures, such as IBI or SDNN, may be more suitable. Further investigation is necessary to determine the specific mechanisms underlying the observed trends in HR variability during nighttime work shifts. Besides, future research could focus on investigating the impact of environmental factors, such as temperature, noise, and light exposure, on HRV during nighttime work shifts, as well as the impact of sleep quality and duration on HRV. (Stephenson et al., 2021).

6. Conclusion

This study aims to investigate the impact of various factors, such as day-night conditions and time progressing, on the fatigue levels of remote operators controlling MASS. To accomplish this, a simulated remote navigation experiment was performed to measure the mental workload and fatigue level of operators. The results of the study showed that the workload and fatigue levels of remote operators were influenced by various factors, such as the time of day, task complexity, and the duration of time on task. The study also identified the need for a shift design that can minimise potential safety issues caused by fatigue and abnormal workloads, ensuring the safe and efficient operation of MASS.

Overall, this study provides valuable insights into the design and operation of RCCs for MASS. The findings can inform the development of guidelines and policies for the operation of MASS, particularly in terms of shift configurations and workload management. Further research can build on this study by exploring the impact of additional factors, such as the operator's experience and training, on workload and fatigue levels. Additionally, future studies can investigate the effectiveness of interventions such as rest breaks and task rotation in reducing operator fatigue.

Acknowledgement

The research is sponsored by the National Key R&D Program of China (2022YFE0115000), the Funds for International Cooperation and Exchange of the National Natural Science Foundation of China (51920105014), and the innovation and entrepreneurship team import project of Shaoguan City (201208176230693). It is also partially supported by the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie (ENHANCE, 823904).

References

1) Åkerstedt, T., & Gillberg, M. (1990). Subjective and objective sleepiness in the active individual. The International Journal of Neuroscience, 52 1-2, 29–37.
2) Alsos, O. A., Veitch, E., Pantelatos, L., Vasstein, K., Eide, E., Petermann, F.-M., & Breivik, M. (2022). NTNU Shore Control Lab: Designing shore control centres in the age of autonomous ships. Journal of Physics: Conference Series, 2311(1), 012030. https://doi.org/10.1088/1742-6596/2311/1/012030
3) Buchheit, M. (2014). Monitoring training status with HR measures: Do all roads lead to Rome? Frontiers in Physiology, 5, 73.
4) Burgess, H. J., Trinder, J., Kim, Y., & Luke, D. (1997). Sleep and circadian influences on cardiac autonomic nervous system activity. American Journal of Physiology-Heart and Circulatory Physiology, 273(4), H1761–H1768. https://doi.org/10.1152/ajpheart.1997.273.4.H1761
5) Charles, R., & Nixon, J. (2019). Measuring mental workload using physiological measures: A systematic review. APPLIED ERGONOMICS, 74, 221–232. https://doi.org/10.1016/j.apergo.2018.08.028
6) Chouchou, F., & Desseilles, M. (2014). Heart rate variability: A tool to explore the sleeping brain? Frontiers in Neuroscience, 8, 402.
7) Fraunhofer, C. (2016). Maritime unmanned navigation through intelligence in networks. Fraunhofer CML: Hamburg, Germany.
8) Glaros, Z., Carvalho, R. E., & Flynn-Evans, E. E. (2021). An Evaluation of Sleepiness, Performance, and Workload Among Operators During a Real-Time Reactive Telerobotic Lunar Mission Simulation. Human Factors: The Journal of the Human Factors and Ergonomics Society, 001872082110567. https://doi.org/10.1177/00187208211056756
9) Hancock, G.M., Longo, L., Young, M.S. and Hancock, P.A. (2021). MENTAL WORKLOAD. In HANDBOOK OF HUMAN FACTORS AND ERGONOMICS (eds G. Salvendy and W. Karwowski). https://doi.org/10.1002/9781119636113.ch7
10) Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. In P. A. Hancock & N. Meshkati (Eds.), Advances in Psychology (Vol. 52, pp. 139–183). North-Holland. https://doi.org/10.1016/S0166-4115(08)62386-9
11) Kerkamm, F., Dengler, D., Eichler, M., Materzok-Köppen, D., Belz, L., Neumann, F. A., Zyriax, B. C., Harth, V., & Oldenburg, M. (2021). Measurement Methods of Fatigue, Sleepiness, and Sleep Behaviour Aboard Ships: A Systematic Review. International Journal of Environmental Research and Public Health, 19(1), 120. https://doi.org/10.3390/ijerph19010120
12) Koenig, J., Jarczok, M., Ellis, R., Hillecke, T., & Thayer, J. F. (2014). Heart rate variability and experimentally induced pain in healthy adults: A systematic review. European Journal of Pain, 18(3), 301–314.
13) Li, K. W., Peng, L., Zhao, C., & Khaday, S. (2022). Mental workload assessments of aerial photography missions performed by novice unmanned aerial vehicle operators. Work, 1–13. https://doi.org/10.3233/WOR-211222
14) Lindstad, H., Verbeek, R., Blok, M., Van Zyl, S., Hübscher, A., Kramer, H., Purwanto, J., Ivanova, O., & Boonman, H. (2015). GHG emission reduction potential of eu-related maritime

transport and on its impacts.(Ref: CLIMA. B. 3/ETU/2013/0015). TNO Report.

15) Longo, L. (2017). Subjective Usability, Mental Workload Assessments and Their Impact on Objective Human Performance. In: Bernhaupt, R., Dalvi, G., Joshi, A., K. Balkrishan, D., O'Neill, J., Winckler, M. (eds) Human-Computer Interaction - INTERACT 2017. INTERACT 2017. Lecture Notes in Computer Science, vol 10514. Springer, Cham. https://doi.org/10.1007/978-3-319-67684-5_13
16) Man, Y., Lundh, M., Porathe, T., & MacKinnon, S. (2015). From Desk to Field—Human Factor Issues in Remote Monitoring and Controlling of Autonomous Unmanned Vessels. Procedia Manufacturing, 3, 2674–2681. https://doi.org/10.1016/j.promfg.2015.07.635
17) Man, Y., Weber, R., Cimbritz, J., Lundh, M., & MacKinnon, S. N. (2018). Human factor issues during remote ship monitoring tasks: An ecological lesson for system design in a distributed context. International Journal of Industrial Ergonomics, 68, 231–244. https://doi.org/10.1016/j.ergon.2018.08.005
18) Marchand, C., De Graaf, J. B., & Jarrassé, N. (2021). Measuring mental workload in assistive wearable devices: A review. Journal of NeuroEngineering and Rehabilitation, 18(1), 160. https://doi.org/10.1186/s12984-021-00953-w
19) Peng, L., & Li, K. W. (2022). Perceived difficulty, flight information access, and performance of male and female novice drone operators. Work, 72(4), 1259–1268. https://doi.org/10.3233/WOR-210862
20) Ramos, M. A., Utne, I. B., & Mosleh, A. (2019). Collision avoidance on maritime autonomous surface ships: Operators' tasks and human failure events. Safety Science, 116, 33–44. https://doi.org/10.1016/j.ssci.2019.02.038
21) Reyes del Paso, G. A., Langewitz, W., Mulder, L. J., Van Roon, A., & Duschek, S. (2013). The utility of low frequency heart rate variability as an index of sympathetic cardiac tone: A review with emphasis on a reanalysis of previous studies. Psychophysiology, 50(5), 477–487.
22) S. Guan, J. Wang, C. Jiang, X. Hou, Z. Fang and Y. Ren, "Efficient On-Demand UAV Deployment and Configuration for Off-Shore Relay Communications," 2021 International Wireless Communications and Mobile Computing (IWCMC), Harbin City, China, 2021, pp. 997-1002, doi: 10.1109/IWCMC51323.2021.9498601.
23) Schnell, I., Potchter, O., Epstein, Y., Yaakov, Y., Hermesh, H., Brenner, S., & Tirosh, E. (2013). The effects of exposure to environmental factors on Heart Rate Variability: An ecological perspective. Environmental Pollution, 183, 7–13. https://doi.org/10.1016/j.envpol.2013.02.005
24) Stephenson, M. D., Thompson, A. G., Merrigan, J. J., Stone, J. D., & Hagen, J. A. (2021). Applying Heart Rate Variability to Monitor Health and Performance in Tactical Personnel: A Narrative Review. International Journal of Environmental Research and Public Health, 18(15), 8143. https://doi.org/10.3390/ijerph18158143
25) van den Broek, H., & van der Waa, J. (2022). Intelligent Operator Support Concepts for Shore Control Centres. Journal of Physics: Conference Series, 2311(1), 012032. https://doi.org/10.1088/1742-6596/2311/1/012032
26) Y. Zhang, G. Zhao, Y. Shu, Y. Ge, D. Zhang, Y. -J. Liu, & X. Sun. (2021). CPED: A Chinese Positive Emotion Database for Emotion Elicitation and Analysis. IEEE Transactions on Affective Computing, 1–1. https://doi.org/10.1109/TAFFC.2021.3088523
27) Young, M. S., Brookhuis, K. A., Wickens, C. D., & Hancock, P. A. (2015). State of science: Mental workload in ergonomics. Ergonomics, 58(1), 1–17. https://doi.org/10.1080/00140139.2014.956151
28) Zhang, X., Wang, C., Chui, K. T., & Liu, W. (2021). A real-time collision avoidance framework of MASS based on b-spline and optimal decoupling control. Sensors, 21(14). https://doi.org/10.3390/s21144911