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IDENTIFYING THE INFLUENCE OF LAND LOGISTIC DRIVER COGNITIVE ENERGY IMPACT ON SUPPLY CHAIN PERFORMANCE THROUGH AGENT-BASED SIMULATION

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Logistic transports link demand generators, distributors, and producers in a supply chain network (SCN). The existence of logistic transports is critical to ensure whole nodes' economic sustainability. This study explores the impact of human factors on SCN performance through cognitive energy expenditure (CEE) tracking. Agent-based model (ABM) simulation was used to analyze the impact of CEE from truck driver's electroencephalography (EEG) data to obtain the postsynaptic potential values, which were then transformed to calorific energy. The fleet agents, retailers and distributor models were built based on the East Java, Indonesia, logistic transport route around Karanglo, Gempol, Bungurasih, and Gubeng. The frequency and the peak value of the EEG data, postsynaptic potential, and energy data indicate the same information. All data indicate that more challenging routes have higher frequency and higher peak values. The ABM simulation of the fleet agents shows balanced CEE throughout entire routes due to the precise rest period and eat scheduling. The average delivery success rate was 8 out of 30 or 26.7 % in each simulation time step. Hence, most goods delivery tasks can be completed by fleet agents in a balanced system. As a consequence, the SCN performance is also balanced due to the fluid inventory shift without overstock and stockouts. The rest and eat periods of a fleet agent were scheduled after the CEE has been peaked. The time lag between rest periods and transport operations has to be maintained to overcome fleet agents task buildup. Task buildup has a potential to decay both transport safety and inventory shift rates. Therefore, the upgrade in SCN performance is possible through proper fleet agents scheduling

Keywords: cognitive energy expenditure (CEE), supply chain network (SCN), agent-based simulation, electroencephalography (EEG), logistic transport

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1. Introduction

The performance of a supply chain network (SCN) is determined by various multidimensional factors. As a fully connected network that consists of many entities, SCN has become the most important driver of the global economy [1]. Manufacturing centers (MC), distributors, stores, and customers are connected through logistic transports. Logistic transports are the main driver of the SC network, the disruption in the SC network could collapse the entire SC network [2]. Logistic transport also intersects with various supporting factors including the human factor (HF) [3]. HF determines the fluidity of transport operations, the occurrence of an accident or another movement inhibition factor affects the key performance indicators (KPI) of an SCN. The delivery time of a transport operation has to be balanced with the tact time of a manufacturing system and inventory shift frequency. The common SCN KPI such as the cash-to-cash (C2C) cycle clearly shows the dependencies on the holistic regularity of the SCN. C2C value gets higher as the inventory shift frequency increases such as practiced in the just-in-time (JIT) inventory control paradigm [4].

Human factors determine the success of human-reliant tasks such as land logistic transport. Cognition is tied to every human-controlled or human-related activity that involves cognition [5]. Cognitive processes consist of conscious and unconscious processes. Conscious processes require vigilance to be performed while unconscious processes do not [6]. During cognition, the cognitive load increases. Too much cognition causes a cognitive overload situation where the amount of information processing is high, which possibly causes overwhelms. On the other hand, low information processing triggers a cognitive underload situation where a person cannot focus on a simple task [7]. The information load is directly linked to cognitive energy usage as cognitive processes are the result of neuron firing [8].

The KPI of an SCN can quantitatively be modeled with a simple symbolic mathematics. Computer simulation has been a versatile tool that enables real-world object modeling and simulation using simple quantitative algorithms [9]. The modeling of a complex system was started in the 1940s by John Von Neumann, which resulted in a cellular automata theorem, which later on developed into self-reproducing automata [10]. The further development of Von Neumann's automata to model highly complicated processes was performed by John Conway in the 1960s through the development of Conway's game of life [11]. In the 1980s, the invention of object-oriented programming (OOP) eases the modeler to replicate the real-world object in a computer program [12]. The major system modeling paradigms with computer simulation are system-dynamics, discrete event simulation (DES), and agent-based simulation. DES and agent-based simulation are fit for quantitative system modeling with a high amount of detail. DES relies on statistical distribution formed by the process [13]. Meanwhile, the agent-based model (ABM) implements OOP that allows each agent to have its own logic [14]. Hence, the computer simulation provides a control mechanism for an SCN model. Therefore, research on the development of an ergocentric ABM simulation system integrated with the human-brain interface improves the KPI completeness.

2. Literature review and problem statement

Computer simulation has been used in SCN modeling, design, and analysis. The common usage of computer simulation for SCN is to predict the effect of a strategy on KPI prior to implementation. The study [15] implements the analysis of Europe environmental policy assessment impact on logistic transport efficiency. The result of the simulation was a controllable variables combination such as emissions, cost, lead time, and delivery time to define actions that should be taken to improve SCN performance during the policy implementation. Various control factors effect analysis in a system can be used as a basis to build a decision support system. However, no modification to standard KPI was performed by the control application provided. This study performs direct modification to the existing KPI based on the simulation results. The simulation of a valid model outputs approximately near result to the implementation [16].

Computer simulation is useful for multi-factor SCN design. A multi-constraint urban logistic transport system requires the model to cover every single factor that would affect the entire SCN [17]. Traffic lights and crossing pedestrians may slow down vehicle movement, which increases delivery time. The ABM allows each vehicle to experience the traffic while its data are logged. As a result, the ABM simulation enables action planning and the action outcome estimation before the actual action has been performed [18]. Moreover, ABM can mimic the actual object without relying on statistical distributions, which facilitates the properties or attributes attachment of the modeled objects [19]. Therefore, ABM allows more flexible logic constructions over DES.

The architecture of the ABM provides modularity, which eases the integration of a simulation model with another model. The study [20] shows ABM model integration with DES results in a realistic stochastic process that enables various responses according to the DES simulation. Such models are testable through some predefined scenarios, which can be optimized to find the best variable settings. The study [21] performs further optimization of such models through analytical methods, which helped in the urban goods transport planning in Rotterdam, Netherlands. The study [22] includes environmental factors to optimize the model. However, all of the mentioned studies do not involve any economic metric. This study adds SCN KPI to the simulation model, which can be the economic metric for the data-driven simulation. The simulation found the best pattern for freight transport routing inside a city or town.

Data-driven simulation allows the model to include the human factor to predict human-related process behavior. The vehicle routing process is a human-related process when vehicles are non-autonomous. The human controls are varied in nature so that the outcome of a process handled by a person may differ with another person [23]. Statistically, the human-related process is often modeled with normal distribution while the machine-related process obeys uniform distribution [24]. Further challenge is not to model the human action in a simulated environment but to model more detailed sub processes such as biological processes with a single model. A common technique to analyze biological processes is through external simulation environment integration [25]. This study presents a novel approach by integrating electroencephalography (EEG) data with GIS-based Agent-Based Modeling (ABM) simulation to develop a robust Spatial Cognitive Network (SCN) that incorporates human factors. The integration of EEG, a powerful tool for measuring brain activity, with ABM simulation techniques allows for a deeper understanding of how human cognition influences spatial behaviors within the simulated environment. All this allows us to assert that it is expedient to conduct a study on the integration of the simulation cognitive processes, and spatial decision-making.

3. The aim and objectives of the study

The aim of this study is to obtain factors for optimal land logistic driver action control. This will make it possible to control the transport scheduling process based on human factors.

To achieve the aim, the following objectives were accomplished:

– to investigate the relation between cognitive human factors and SCN performance;

– to explore the effect of logistic transport driver actions configuration on SCN performance;

– to optimize the delivery process based on driver energy.

4. Materials and methods

The primary focus of this study is to integrate electroencephalography (EEG) data with GIS-based Agent-Based Modeling (ABM) simulation to develop a robust Spatial

Cognitive Network (SCN) that incorporates human factors. The main hypothesis of this study posits that integrating EEG data into GIS-based ABM simulation will lead to a more accurate and behaviorally realistic model of spatial cognition within a simulated environment. In conducting this research, certain assumptions were made regarding the compatibility and integration of EEG data with ABM simulation techniques, as well as the validity of cognitive processes represented in the simulation based on EEG measurements. To facilitate the integration process and streamline the simulation, simplifications were adopted in the representation of cognitive states and their interactions within the SCN, while ensuring that essential aspects of human cognition and spatial behaviors are captured effectively.

The human factors data required for land logistic driver energy tracking were EEG and location data. The EEG data were obtained from direct recording with a dry EEG electrode Neurosky Mindwave Mobile V2 through a notebook computer with the Windows 10 operating system. The amplitude of EEG was measured by calculating the square root of the EEG data with equation (1). The frequency domain EEG data were then transformed to time domain data through inverse Fourier transform in equation (2). The amplitude of the EEG data was then used as the basis to obtain the wave transversal speed using equation (3). The time domain postsynaptic potential data can be obtained by using equation (4). The data were converted into calorific energy through equation (5):

$$A_{EEG}=\sqrt{EEG}\left(\mathrm{mV}\cdot\mathrm{Hz}^{-1}\right), \tag{1}$$

$$EEG_{(t)}=\frac{1}{2\pi}\int_{-\infty}^{\infty} EEGe^{j\omega t}\partial\omega\left(\mathrm{mV}^2\mathrm{s}^{-1}\right), \tag{2}$$

$$\omega=2\pi f, \tag{3}$$

$$PSP=\sum_{i=1}^{\infty} A_{EEG}\sin\left(\omega_i t+\theta_i\right)\left(\mathrm{mJ}\cdot\mathrm{s}^{-1}\right), \tag{4}$$

$$PSP_{cal}=0.00024\times PSP\left(\mathrm{cal}\cdot\mathrm{s}^{-1}\right), \tag{5}$$

where A_{EEG} is the amplitude of EEG frequency data, $EEG_{(t)}$ is the time-domain EEG data, ω is the brainwave velocity, *PSP* is the postsynaptic potential value.

The energy data were then used to evaluate the driver's condition during transport. The evaluation scope was limited to driver energy tracking. The simulation logic was modeled with the built-in AnyLogic state-chart written in the Java programming language. There were 3 states of a vehicle modeled in the simulation. The states were atDistributor, moveToRetailer, and moveToDistributor. In atDistributor, the driver agents gained energy intake because they were assumed to take a rest period and eat during rest. In moveToRetailer and moveToDistributor, the driver agents spent their energy to perform delivery. The logic of each state is shown in pseudocode 1:

Pseudocode 1. Vehicle agents state-chart transition logic:
1. Truck, Distributors, Retailers agents initialized
2. Integer Retailers.generateDemands()
3. String msg=new msg(Distributors)
4. Order order=Distributor.generateOrder(msg)
5. While simulation.Run=True:
6. If Truck.onState(atDistributor)
7. BMR +=sleepEnergy + eatEnergy – CEE
8. Else if Truck.onState(moveToRetailer)
9. BMR -=CEE
10. Else if Truck.onState(atRetailer)
11. BMR +=sleepEnergy + eatEnergy – CEE
12. Else if Truck.onState(moveToDistributor)
13. BMR -=CEE
14. Else
15. Simulation.Run=False

The logistic transport routes were obtained from the East Java route around Karanglo, Gempol, Bungurasih, and Gubeng highways. The simulation model understands the location through geographical information system (GIS) built-in package integration with openstreetmap (OSM) data. The data contain real EEG recording data of the drivers.

The supply chain performance analysis in the model was performed through inventory shift analysis. The inventory shifts were determined by the order generated by retailers. Each retailer generates an order for the distributor through a message event system that produces random demands. The message was instantiated as an object received by the distributor.

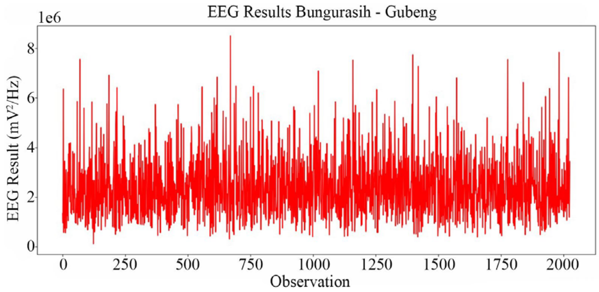
5. Results of the cognitive human factor effect on the SCN performance

5. 1. The relationship investigation results between cognitive human factors and SCN performance

The EEG results indicates the challenge faced by drivers during the transport operation. The EEG results are presented in Fig. 1, which shows the squared value of postsynaptic potential values over frequency. The x-axis of the plot represents the number of observations during data collection. The Bungurasih-Gubeng route is the longest because the observation number is more than 2,000 while for the other routes only around 1,000 (Fig. 1, *a*). Bungurasih-Gubeng is also the hardest route among all the observed routes as it produces the highest EEG peak value, which is more than 8.0 Volts^2/Hz while the Gempol-Bungurasih route only around 6.5 Volts^2/Hz (Fig. 1, *b*), and Karanglo-Gempol about 7.0 Volts^2/Hz (Fig. 1, *c*).

The recorded EEG data represent the cognitive dynamics of a land logistic driver. Cognitive dynamics is a branch of neuroscience that studies brain activity or collective neuron activity such as postsynaptic neuronal dynamics in EEG [26]. More insights can be obtained from a collection of neurons instead of a single neuron analysis. In the case of land logistic driver activity, the cognitive dynamics represent the vigilance requirements on a certain route. The results indicate that the condition of a route affects the driver's response. Such condition occurred due to the brain's non-stop information processing in beta and alpha states [27]. However, in the gamma state the brain vigilance may be halted, which triggers a flow phenomenon. Flow is a condition when a person gives full attention towards an object, performance, or anything that causes them unaware of the environmental situation [28]. Therefore, a higher EEG value indicates more postsynaptic connection activation to process information from situational response.

The postsynaptic response can be tracked from the postsynaptic potential value. As the transformation from EEG results, the postsynaptic potential gives similar insights. However, the insights become clearer as the voltage data can be thought of as an active and inactive process such as binary representation in electronics [29]. From Fig. 2, *a*, the Bungurasih-Gubeng route shows a level higher postsynaptic potential compared to Gempol-Bungurasih (Fig. 2, *b*) and Karanglo-Gempol (Fig. 2, *c*). The postsynaptic potential shift pattern of the Bungurasih-Gubeng route also shows a more frequent shift at the time domain level compared to other routes.



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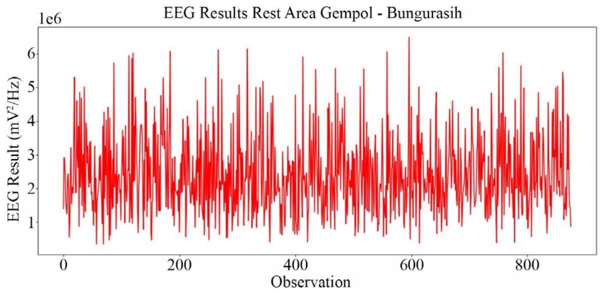

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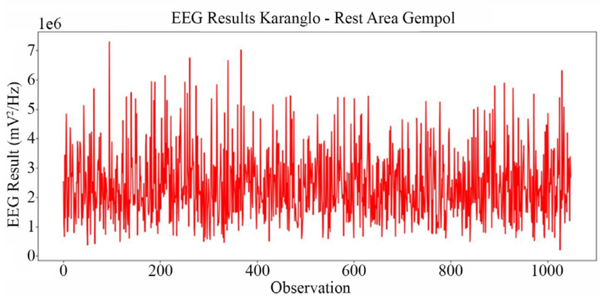

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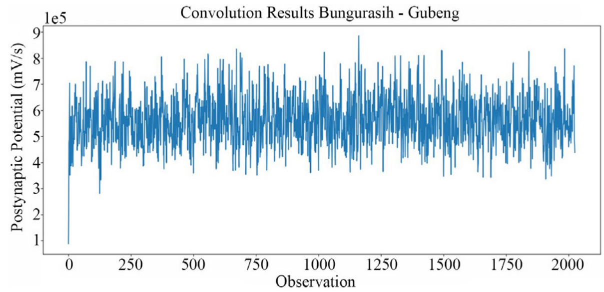
Fig. 1. EEG recording results of truck drivers: *a* — Bungurasih to Gubeng route; *b* — Gempol to Bungurasih route; *c* — Karanglo to Gempol route

The frequent postsynaptic potential shift indicates frequent information processing and retrieval. The change in postsynaptic values shows the amount of the collective neuronal dynamics activity in synapses. The phenomenon was extracellular and intracellular ion exchange. There are 4 potassium ions from the intracellular region that exchanged with a sodium ion [30]. The ion exchange process was through a proton pump that has to be activated with adenosine tri-phosphate (ATP), which is a currency of human energy in metabolism [31]. Three ATP have to be released each time the pumping process started, which open the intracellular-extracellular region interface [5]. During the ion exchange process, the diffusion between two regions occurred, which enforces the ion concentration to stabilize the effect. Diffusion is a transport mechanism in which substances in the higher concentration region move towards the lower concentration regions [32]. Consequently, the impact of the collective neuronal dynamics phenomenon is cognitive energy expenditure (CEE).



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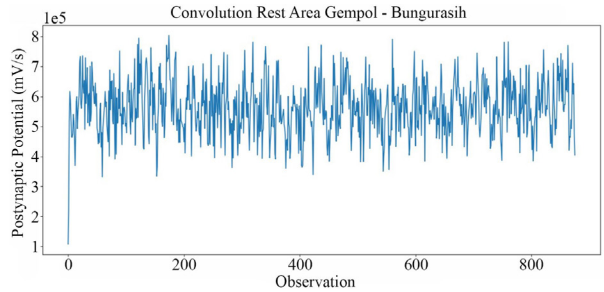

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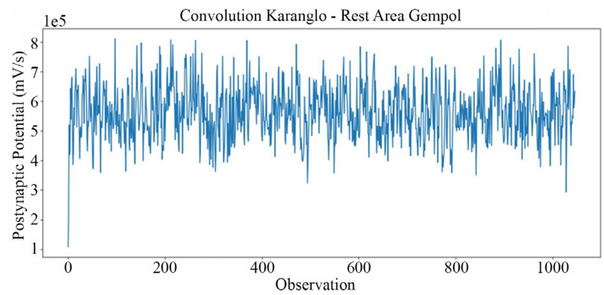

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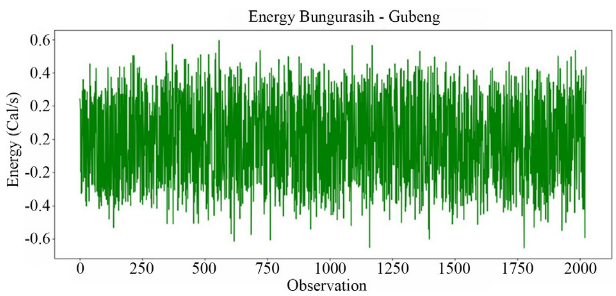
Fig. 2. Postsynaptic potential plot of truck drivers: *a* — Bungurasih to Gubeng route; *b* — Gempol to Bungurasih route; *c* — Karanglo to Gempol route

According to the CEE phenomenon, the energy expenditure of some tasks performance in a certain period of time can be predicted through brain activity. EEG results can be used to track brain activity during a physical or cognitive task performance [33]. Hence, the results of EEG recording of the driving task on each route were converted to calories using equation (5). The results were plotted in Fig. 3 where Fig. 3, *a* is the Bungurasih-Gubeng route, Fig. 3, *b* Gempol-Bungurasih, and Fig. 3, *c* Karanglo-Gempol. The caloric patterns of each data are equal to the postsynaptic potential patterns. The Bungurasih-Gubeng data still form the same frequency pattern with the highest energy peak among others. Therefore, the Bungurasih-Gubeng route requires slightly more energy compared to the other measured routes.

The CEE depends on decision-making and situational response activities. Both define the cognitive load of a land vehicle driver, which also determines driving performance [34]. The performance largely depends on efficient situational response, which requires long-term vigilance. The vigilance itself drives the executive function to sustain concentration [35]. During the performance of the executive function, the information perception is higher, which results in greater ion exchange. As a result, the energy frequency shift is higher. Meanwhile, the complexity of the task defines the peak of the postsynaptic response, which forms a linear simultant relationship with the CEE.



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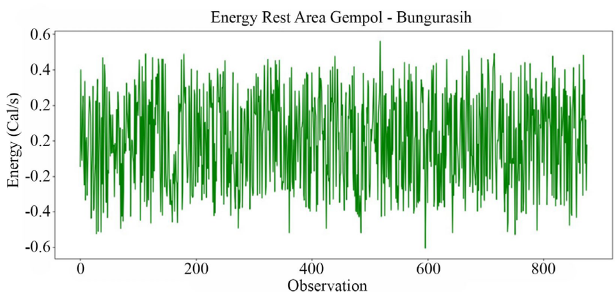

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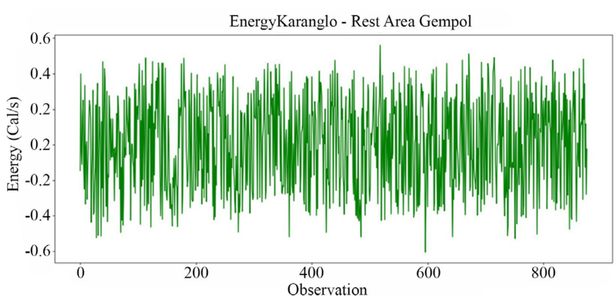

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Fig. 3. CEE plot of truck drivers:
a – Bungurasih-Gubeng route; *b* – Gempol-Bungurasih route; *c* – Karanglo-Gempol route

5. 2. Exploration of logistic transport driver actions configuration

The ABM simulation animation view represents the location information precisely. The order fulfillment operations during transport can be tracked from the interactive GIS scene as shown in Fig. 4.

The green building icon represents the retailer location. The yellow building icon is a distributor that has 30 truck fleet agents. Based on Fig. 4, it is also can be seen that the routes were close to each other. Automatically, each fleet agent chooses the shortest path to reach the end node. The GIS map is a linear graph connection that connects one location node to another [36]. Hence, the agents are optimized with efficient time complexity in operation.

The efficient graph path finding by the agents in the constructed model indicates that the model is capable of real-world interaction. The virtual real world interaction requires real-time data transaction in which data are exchanged over time from a device to the model [37]. This makes real-time data-driven model building possible. The interaction between a virtual object model that mimics the object features including its functions in the real world is called a cyber-physical system [38]. The expandability of the ABM model makes the feature mimicking process easy, which allows the model to directly capture physical information. Therefore, the constructed ABM model is suitable for the cyber-physical system of an SCN.

5. 3. Optimization of the delivery process based on driver energy

During simulation runtime, the CEE pattern in each state was logged as in Fig. 5. The calorific energy expenditure pattern is balanced as shown in Fig. 5. Sleeping and eating increase energy intake, which reduces the gap between the energy spent and basal metabolic rate (BMR). The results in Fig. 5 do not include BMR due to variations in BMR. The value of BMR depends on various biological factors such as age, body weight, muscle mass, and many other factors [39]. In order to avoid bias, this study limits the view on BMR by assuming each truck driver has the same BMR.

In the simulation, the CEE is immediately covered by the energy intake. Energy intake from foods and physical recovery from sleep and naps are critical to maintain alertness during low cognitive load tasks such as driving at low speed. A sharp mind is required for decision-making processes such as deciding the best driving strategy on a certain road in a certain condition [40]. The best driving strategy outputs the safest and most efficient route. Current simulation results average 8 fulfilled orders in a single step out of 30 deliveries or 26.7 % in each simulation. However, the reordering events are random so the amount of the order could be below current orders or above current orders. Order fulfillment occurred when the energy expenditure reaches its peak. Each order fulfillment is followed by peak energy intake, which is used in the next process. Consequently, the inventory shift pattern follows the shift of CEE and energy intake. Hence, the inventory shift is defined by the order fulfillment process determined by the driving strategy.

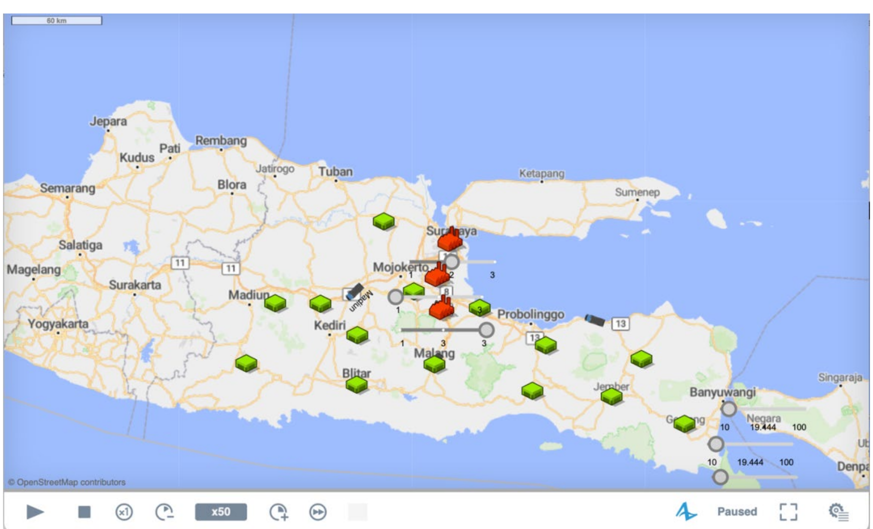

Fig. 4. Animation view of the simulation results

The simulation found the best pattern to maintain a stable SCN performance. The SCN performance can be maintained through HF management in logistic transport. The HF management is based on the CEE pattern that can be controlled through the proper rest period scheduling for distributors and retailers. The transport operation is in the most balanced state when the most exhaustive operation is closest to the rest schedule. The duration of the rest period also needs to be determined according to the most exhaustive task.

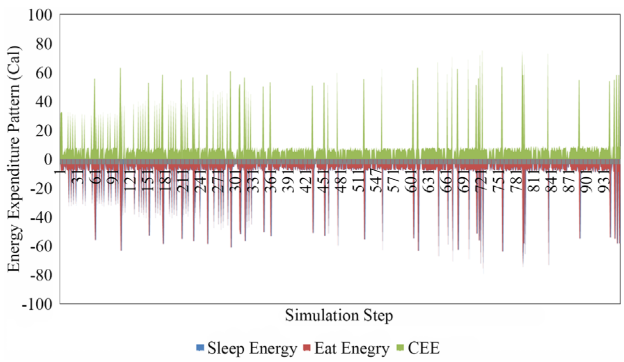

Fig. 5. Cognitive energy expenditure pattern during the simulation process

The constructed ABM model can act as a cyber-physical system for SCN optimization. However, the SCN performance tracking based on driver performance only cannot provide reliable prediction all the time. The inaccuracy of the model may flex the prediction results. The accuracy of the model depends on the historical data volume and traffic data integration. Even though the EEG data represent the situational response, the route familiarity reduces the brain activity to decide actions when capturing information. Hence, there are some complexities that need to be reduced to build an accurate real-time model. The reinforcement learning model can reduce the large data volume requirement while responding to the situation according to the driver's experience.

6. Discussion of the cognitive human factor effect on the SCN performance

This study investigated the relationship between cognitive human factors and Supply Chain Network (SCN) performance in logistic transports. EEG data were used as an indicator of Cognitive Energy Expenditure (CEE) to assess driver fatigue and workload on different routes. The results showed a clear correlation between challenging routes and higher CEE, as indicated by increased EEG frequency and peak value (Fig. 1). For instance, the Bungurasih–Gubeng route, which was the longest route in the study, exhibited the highest EEG peak value (Fig. 1, *a*).

An Agent-based Model (ABM) simulation was developed to analyze how driver CEE impacts SCN performance. The model incorporated real-world elements such as rest periods, meal scheduling, and route optimization (Fig. 4). The simulation results demonstrated that proper scheduling based on CEE peaks can lead to a balanced workload for drivers and ensure successful task completion. The average delivery success rate achieved in the simulation was 8 deliveries out of 30 per time step (26.7 %), indicating efficient order fulfillment. This balanced approach to scheduling also ensured smooth inventory flow by preventing stockouts.

The findings of this study highlight the importance of Human Factors (HF) management in logistic transport operations. By monitoring CEE and implementing proper rest periods based on workload peaks, SCN performance can be significantly improved. The ABM simulation serves as a valuable tool for optimizing SCN performance through HF management.

However, it is important to acknowledge limitations in the model's accuracy. Factors such as historical data volume, traffic data integration, and driver familiarity with routes can all influence the model's predictive capabilities. EEG data, while effective in capturing situational response, may not fully account for the reduced brain activity experienced by drivers familiar with a route.

To address these limitations and achieve a more robust real-time model, future research could explore incorporating reinforcement learning. This approach could potentially reduce the reliance on large data volumes while enabling the model to adapt to dynamic situations based on driver experience. Overall, this study provides valuable insights into the impact of driver CEE on SCN performance and paves the way for further development of real-time optimization models that consider both human factors and operational efficiency.

While this research offers a promising ABM simulation for optimizing SCN performance through driver CEE, limitations exist. The model's accuracy relies heavily on historical data volume, traffic integration, and driver route familiarity. EEG data may not fully capture the impact of route familiarity on brain activity. Future research incorporating reinforcement learning could address these limitations by reducing reliance on large datasets and enabling adaptation to driver experience for a more robust real-time optimization model.

One disadvantage of this study is that it solely relied on EEG data to assess driver fatigue. While EEG provides valuable insights into cognitive load, it doesn't capture the full picture of driver fatigue. Factors like sleep quality, pre-existing health conditions, and individual tolerance to workload can all influence fatigue levels. Future studies could incorporate additional measures like subjective fatigue surveys or physiological data like heart rate variability to provide a more comprehensive understanding of driver fatigue and its impact on SCN performance.

Building upon this study, future research can explore incorporating real-time traffic data and driver experience into the ABM simulation. This could involve implementing reinforcement learning algorithms. However, challenges lie in developing efficient algorithms that can handle the dynamic nature of traffic data and translate driver experience into adaptable decision-making within the simulation. Additionally, ensuring the privacy and security of real-time driver data during collection and integration will be crucial.

7. Conclusions

1. The SCN performance is defined by inventory shift, which is also defined based on driver performance. Driver performance peaked during the order fulfillment process when the fleet agents reach a distributor node or a retail node. The driver performance was indicated by the peaked CEE. The CEE reaches the maximum value of 60 cal during the order fulfillment process.

2. The inventory shift pattern is determined by the CEE-energy intake shifting pattern, which should always be balanced. Drivers always rest and eat after fulfilling orders. Therefore, the balance of SCN performance should always be maintained. The total energy of the energy input from sleeping and eating always balanced the total output energy.

3. The output of the simulation shows the control variables that can be optimized to improve SCN performance and truck driver's safety. The rest and eat pattern of a fleet agent must be optimized whenever the CEE pattern becomes chaotic. The chaotic pattern is defined by the extreme calorific change of energy expenditure from 15, 16, and back to 15 cal. The frequency of the longitudinal waveform plot pattern between the simulation step and CEE indicates the frequency of energy expenditure.

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.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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References

1. Essakly, A., Wichmann, M., Spengler, T. S. (2019). A reference framework for the holistic evaluation of Industry 4.0 solutions for small-and medium-sized enterprises. IFAC-PapersOnLine, 52 (13), 427–432. https://doi.org/10.1016/j.ifacol.2019.11.093
2. Wang, S., Jiang, Z., Noland, R. B., Mondschein, A. S. (2020). Attitudes towards privately-owned and shared autonomous vehicles. Transportation Research Part F: Traffic Psychology and Behaviour, 72, 297–306. https://doi.org/10.1016/j.trf.2020.05.014
3. Walker, G., Strathie, A. (2016). Big data and ergonomics methods: A new paradigm for tackling strategic transport safety risks. Applied Ergonomics, 53, 298–311. https://doi.org/10.1016/j.apergo.2015.09.008
4. Dunn, N., Williamson, A. (2012). Mitigating the effects of monotony. Rail Human Factors around the World, 774–782. https://doi.org/10.1201/b12742-87
5. Gerstner, W., Kistler, W. M., Naud, R., Paninski, L. (2014). Neuronal Dynamics. Cambridge University Press. https://doi.org/10.1017/cbo9781107447615
6. Balfe, N. (2020). Human factors applications of on-train-data-recorder (OTDR) data: an exploratory study. Cognition, Technology & Work, 23 (2), 239–253. https://doi.org/10.1007/s10111-019-00622-y
7. Basacik, D., Waters, S., Reed, N. (2015). Detecting Cognitive Underload in Train Driving: A Physiological Approach. The Fifth International Rail Human Factors Conference. Available at: https://programme.exordo.com/rhf2015/delegates/presentation/42/
8. Zhang, X., Li, J., Liu, Y., Zhang, Z., Wang, Z., Luo, D. et al. (2017). Design of a Fatigue Detection System for High-Speed Trains Based on Driver Vigilance Using a Wireless Wearable EEG. Sensors, 17 (3), 486. https://doi.org/10.3390/s17030486
9. Kazil, J., Masad, D. Agent Based Modeling in Python with Mesa. SciPy 2015. Available at: https://www.youtube.com/watch?v=lcySLoprPMc
10. Zaitsev, D. A. (2017). A generalized neighborhood for cellular automata. Theoretical Computer Science, 666, 21–35. https://doi.org/10.1016/j.tcs.2016.11.002
11. Meneghan, L. L. (1976). «Life» a fascinating game. The Arithmetic Teacher, 23 (1), 56–60. https://doi.org/10.5951/at.23.1.0056
12. Joque, J. (2016). The Invention of the Object: Object Orientation and the Philosophical Development of Programming Languages. Philosophy & Technology, 29 (4), 335–356. https://doi.org/10.1007/s13347-016-0223-5
13. Trigueiro de Sousa Junior, W., Barra Montevechi, J. A., de Carvalho Miranda, R., Teberga Campos, A. (2019). Discrete simulation-based optimization methods for industrial engineering problems: A systematic literature review. Computers & Industrial Engineering, 128, 526–540. https://doi.org/10.1016/j.cie.2018.12.073
14. Iannino, V., Mocci, C., Vannocci, M., Colla, V., Caputo, A., Ferraris, F. (2020). An Event-Driven Agent-Based Simulation Model for Industrial Processes. Applied Sciences, 10 (12), 4343. https://doi.org/10.3390/app10124343
15. Sarraj, R., Ballot, E., Pan, S., Hakimi, D., Montreuil, B. (2013). Interconnected logistic networks and protocols: simulation-based efficiency assessment. International Journal of Production Research, 52 (11), 3185–3208. https://doi.org/10.1080/00207543.2013.865853
16. Xu, X., Liu, J., Li, H., Hu, J.-Q. (2014). Analysis of subway station capacity with the use of queueing theory. Transportation Research Part C: Emerging Technologies, 38, 28–43. https://doi.org/10.1016/j.trc.2013.10.010
17. Jlassi, S., Tamayo, S., Gaudron, A. (2018). Simulation Applied to Urban Logistics: A State of the Art. City Logistics 3, 65–87. https://doi.org/10.1002/9781119425472.ch4

18. Zhao, E., Yan, R., Li, K., Li, L., Xing, J. (2021). Learning to Play Hard Exploration Games Using Graph-Guided Self-Navigation. 2021 International Joint Conference on Neural Networks (IJCNN). https://doi.org/10.1109/ijcnn52387.2021.9534251
19. Sert, E., Bar-Yam, Y., Morales, A. J. (2020). Segregation dynamics with reinforcement learning and agent based modeling. Scientific Reports, 10 (1). https://doi.org/10.1038/s41598-020-68447-8
20. Li, J., Rombaut, E., Vanhaverbeke, L. (2021). A systematic review of agent-based models for autonomous vehicles in urban mobility and logistics: Possibilities for integrated simulation models. Computers, Environment and Urban Systems, 89, 101686. https://doi.org/10.1016/j.compenvurbsys.2021.101686
21. de Bok, M., Tavasszy, L. (2018). An empirical agent-based simulation system for urban goods transport (MASS-GT). Procedia Computer Science, 130, 126–133. https://doi.org/10.1016/j.procs.2018.04.021
22. de Bok, M., Tavasszy, L., Sebastiaan Thoen. (2022). Application of an empirical multi-agent model for urban goods transport to analyze impacts of zero emission zones in The Netherlands. Transport Policy, 124, 119–127. https://doi.org/10.1016/j.tranpol.2020.07.010
23. Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G. et al. (2015). Human-level control through deep reinforcement learning. Nature, 518 (7540), 529–533. https://doi.org/10.1038/nature14236
24. Knief, U., Forstmeier, W. (2021). Violating the normality assumption may be the lesser of two evils. Behavior Research Methods, 53 (6), 2576–2590. https://doi.org/10.3758/s13428-021-01587-5
25. Sanz-Leon, P., Knock, S. A., Spiegler, A., Jirsa, V. K. (2015). Mathematical framework for large-scale brain network modeling in The Virtual Brain. NeuroImage, 111, 385–430. https://doi.org/10.1016/j.neuroimage.2015.01.002
26. Hong, S. B., Jung, K.-Y. (2003). Basic Electrophysiology of the Electroencephalography. Journal of the Korean Neurological Association, 21 (3), 225–238. Available at: https://www.jkna.org/upload/pdf/200303001.pdf
27. Jap, B. T., Lal, S., Fischer, P. (2011). Comparing combinations of EEG activity in train drivers during monotonous driving. Expert Systems with Applications, 38 (1), 996–1003. https://doi.org/10.1016/j.eswa.2010.07.109
28. Shepherd, J. (2021). Flow and the dynamics of conscious thought. Phenomenology and the Cognitive Sciences, 21 (4), 969–988. https://doi.org/10.1007/s11097-021-09762-x
29. Street, S. (2016). Neurobiology as Information Physics. Frontiers in Systems Neuroscience, 10. https://doi.org/10.3389/fnsys.2016.00090
30. Schelski, M., Bradke, F. (2017). Neuronal polarization: From spatiotemporal signaling to cytoskeletal dynamics. Molecular and Cellular Neuroscience, 84, 11–28. https://doi.org/10.1016/j.mcn.2017.03.008
31. Vergara, R. C., Jaramillo-Riveri, S., Luarte, A., Moënne-Loccoz, C., Fuentes, R., Couve, A., Maldonado, P. E. (2019). The Energy Homeostasis Principle: Neuronal Energy Regulation Drives Local Network Dynamics Generating Behavior. Frontiers in Computational Neuroscience, 13. https://doi.org/10.3389/fncom.2019.00049
32. Shi, Z., Genack, A. Z. (2018). Diffusion in translucent media. Nature Communications, 9 (1). https://doi.org/10.1038/s41467-018-04242-4
33. Fan, C., Peng, Y., Peng, S., Zhang, H., Wu, Y., Kwong, S. (2022). Detection of Train Driver Fatigue and Distraction Based on Forehead EEG: A Time-Series Ensemble Learning Method. IEEE Transactions on Intelligent Transportation Systems, 23 (8), 13559–13569. https://doi.org/10.1109/tits.2021.3125737
34. Melnicuk, V., Thompson, S., Jennings, P., Birrell, S. (2021). Effect of cognitive load on drivers' State and task performance during automated driving: Introducing a novel method for determining stabilisation time following take-over of control. Accident Analysis & Prevention, 151, 105967. https://doi.org/10.1016/j.aap.2020.105967
35. Lieberman, H. R. (2007). Cognitive methods for assessing mental energy. Nutritional Neuroscience, 10 (5-6), 229–242. https://doi.org/10.1080/10284150701722273
36. Burrough, P. A. (1992). Are GIS data structures too simple minded? Computers & Geosciences, 18 (4), 395–400. https://doi.org/10.1016/0098-3004(92)90068-3
37. Hasan, R. A., Alhayali, R. A. I., Zaki, N. D., Ali, A. H. (2019). An adaptive clustering and classification algorithm for Twitter data streaming in Apache Spark. TELKOMNIKA (Telecommunication Computing Electronics and Control), 17 (6), 3086. https://doi.org/10.12928/telkomnika.v17i6.11711
38. Rezqianita, B. L., Ardi, R. (2020). Drivers and Barriers of Industry 4.0 Adoption in Indonesian Manufacturing Industry. Proceedings of the 3rd Asia Pacific Conference on Research in Industrial and Systems Engineering 2020. https://doi.org/10.1145/3400934.3400958
39. Khonsary, S. (2017). Guyton and Hall: Textbook of Medical Physiology. Surgical Neurology International, 8 (1), 275. https://doi.org/10.4103/sni.sni_327_17
40. Witt, M., Kompaß, K., Wang, L., Kates, R., Mai, M., Prokop, G. (2019). Driver profiling – Data-based identification of driver behavior dimensions and affecting driver characteristics for multi-agent traffic simulation. Transportation Research Part F: Traffic Psychology and Behaviour, 64, 361–376. https://doi.org/10.1016/j.trf.2019.05.007