7. Alyab'eva, O.M. (2020). Organizational and economic mechanism of innovative development of seaports. (Candidate's dissertation). State University of Infrastructure and Technologies, Ukraine. .[in Ukrainian]
8. Horacek, O. & Horovaya, K. Dry port. Features and organization of work. Interlegal. Retrieved from https://interlegal.com.ua/ru/publikacii/suhoj_port_osobennosti_i_organizaciya_raboty/ [in English]
9. Wikipedia (2012). Outport. Retrieved from https://uk.wikipedia.org/wiki/%D0%90%D0%B2%D0%B0%D0%BD%D0%BF%D0%BE%D1%80%D1%82 [in English]

INTELLIGENT APPROACHES TO CREW READINESS ASSESSMENT FOR PORT OPERATIONS IN ERGATIC SHIP SYSTEMS

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Abstract. The integration of software solutions into port operations is increasingly becoming a pivotal factor for ensuring both safety and operational efficiency. However, insufficient crew expertise can significantly impact the psycho-emotional well-being of team members, leading to hazardous situations. The software under consideration employs advanced fuzzy logic and multifactorial algorithms for an in-depth analysis of various parameters, including biometrics, facial expressions, voice tone, text commands, and movement patterns. This comprehensive approach is critically important for accurately assessing risk levels and facilitating prompt decision-making in the dynamic environment of port operations. The modularity of the software and its flexibility in decision-making enable adaptation to the specific requirements of a port, while automation minimizes the potential for human error. Through graphical data visualization, operators gain a lucid understanding of how input variables correlate with risk assessment.

Keywords: Fuzzy logic, port operations, multifactorial assessment, real-time responsiveness, modularity, decision-making flexibility, data visualization, human error minimization.

Introduction. The critical importance of evaluating the operational readiness of ship crews during port operations is an incontrovertible fact that transcends mere considerations of profitability or efficiency. Given that port operations demand a high level of skill and coordination, lapses in attention or incompetence can lead to severe accidents with far-reaching negative consequences not only for the crew but also for the surrounding environment and economic stability [1-3]. Furthermore, the burgeoning growth in global trade and the increasing demands on ports are escalating the performance criteria for crews, thereby heightening the stakes and complicating the challenges they face.

On the other hand, technological advancements offer new avenues for optimizing port operations. Cutting-edge technologies such as automated decision-making systems, integrated diagnostic systems, and artificial intelligence not only have the potential to enhance operational efficiency but also to significantly improve safety measures [4,5]. Therefore, the integration of these technologies into operational processes emerges as a pivotal factor that could substantively impact the overall efficiency and safety of crew-led port operations. It is worth noting the analogous research done on sports teams' readiness, where deep investigations are also carried out [6,7]. Consequently, research on the optimal utilization and adaptation of these technologies within the context of crew readiness is not only relevant but also urgently needed.

Presentation of the core research material and its results. The analysis of information components that define the readiness of crews for port operations in ergatic ship systems necessitates the comprehensive application of appropriate systems and complexes. These can be integrated into a structure termed as the Intelligent Decision Support System (IDSS).

Input Data

1. *Current Technical State of the Ship*: Information collected from sensors and diagnostic systems.

2. *Experience and Qualifications of the Crew*: Database records.

3. *Psycho-Emotional State of the Crew*: Optionally collected via surveys or biometric data.

4. *Environmental Data*: Information such as wind direction, current speed, and the presence of other vessels.

5. Data Processing

6. *Technical Condition Analysis*: Evaluation of the ship's current technical state.

7. *Crew Readiness Assessment*: Comprehensive evaluation of the crew's skills and qualifications.

8. *Environmental Data Collection and Analysis*: Gathering and scrutinizing data regarding the external environment.

9. *Correlational Analysis*: Investigating the relationships between various influencing factors.

Decision Support Algorithms

Scenario Ranking: Creation of a list of potential maneuvering scenarios based on the input data.

Risk Assessment: Evaluation of potential risks associated with each scenario.

Recommendation Module: Selection of the optimal scenario, taking into account all factors and associated risks.

Output Data

Optimal Maneuvering Scenario: Recommendations for docking.

Crew Action Coordination: Guidelines for the optimal orchestration of crew actions.

Technical Equipment Preparation: Checklist of actions required to prepare the technical apparatus.

User Interface

Visual Display: Graphical representation of the optimal maneuver.

Text-Based Instructions and Recommendations: Written guidelines for executing the maneuver.

Audio Signals or Voice Commands: Real-time auditory cues for the crew.

Intelligent decision support system algorithm flow

Data Collection: Gathering all input data either in real-time or manually.

Preliminary Data Processing: Normalization and filtering of collected data.

Data Analysis: Utilizing embedded algorithms for situational assessment.

Scenario Generation: Creating potential scenarios based on the analysis.

Risk Assessment and Recommendations: Selection of the optimal scenario and formation of associated guidelines.

Information Display: Conveyance of recommendations to the crew via the chosen interface.

Data Storage: Archiving all relevant data for future analysis and system training.

During the analysis of input and output data, as well as considering maritime accident analytics, it should be noted that the psychophysiological state of crew members often serves as a decisive factor in assessing the risk of docking in this specific example. This underscores the importance of maintaining the health and well-being of the crew [8].

Application of Intelligent Systems for Psychophysiological State Identification:

Biometric Monitoring: Utilizing sensors to monitor indicators such as pulse, body temperature, and stress levels via skin conductance measurements. These data can be analyzed in real-time to assess an individual's physiological state.

Facial Recognition and Emotion Analysis: Employing cameras and specialized software to scrutinize facial expressions can assist in determining an individual's emotional state.

Voice Analysis: Analysis of voice timbre and speech rate can offer valuable insights into an individual's psychological condition.

Psychomotor Emotional Reaction Monitoring: Utilizing test tasks and psychometric questionnaires adapted for mobile applications to swiftly evaluate an individual's state.

Machine Learning and AI: Training models to analyze gathered data and provide real-time recommendations. These models may even signal the need for crew rotation or work breaks to improve overall state.

Structure of the Computer Program for the AI and Machine Learning Module (Core Components):

Data Sensors and Collectors (Sensors for gathering biometric data; Cameras for facial expression analysis; Microphones for voice analysis).

Data Preprocessing (Noise filtering; Data normalization; Outlier removal).

Database (Storage of collected and processed data).

Machine Learning Module (Training models based on collected data; Algorithms for classifying crew members' states (uncertainty, loss of attention, irritability, apathy, confidence, aggression)).

Recommendation Module (Algorithms for selecting optimal actions (crew rotation, work breaks, additional crew condition checks, etc.)).

User Interface (Dashboard for monitoring crew state; Notification system).

Logging and Reporting System (Data and recommendation history storage; Automated report generation).

Technologies and Implementation Approaches for Psychophysiological Monitoring:

Backend: Utilization of Python programming language with Flask or Django frameworks for API development. TensorFlow and Keras libraries are employed for machine learning algorithms and data processing.

Frontend: JavaScript is used as the primary language for frontend development, with either ReactJS or AngularJS as the chosen framework to facilitate user interaction and data display.

Database System: PostgreSQL or MySQL serves as the repository for data storage, ensuring the integrity and availability of psychophysiological and operational data.

Monitoring System: Grafana is implemented as the monitoring platform, enabling real-time and historical data visualization and analytics.

Notification System: Twilio or SendGrid are utilized for implementing an effective and reliable notification mechanism, capable of alerting relevant parties in real-time.

Algorithm for the intelligent identification of the psychophysiological state of crew members:

Data Acquisition: (Collection of input data from an array of sensors and interfaces).

Data Preprocessing: (Noise elimination to ensure data purity; Normalization to bring varied data metrics to a common scale).

Biometric Data Classification: (Implementation of the Random Forest Classifier to segregate and classify biometric data points).

Facial Expression Analysis: (Utilization of Convolutional Neural Networks (CNN) for nuanced and detailed examination of facial expressions, extracting latent emotional indicators).

Voice Analysis: (Deployment of Support Vector Machines (SVM) for the investigation of vocal tonalities and patterns, which might signal underlying psychological states).

Textual Command Analysis: (Application of Natural Language Processing (NLP) paired with Long Short-Term Memory (LSTM) Networks for in-depth processing and comprehension of textual commands, potentially revealing the cognitive and emotional status of the issuer).

Motion Monitoring: (The K-Nearest Neighbors (K-NN) algorithm is employed to track and understand movement patterns, offering insights into physical state and potential stressors).

Ensemble Models: (Incorporation of ensemble techniques such as Stacking or the Voting Classifier to amalgamate and harmonize the results from various analysis stages, ensuring robust and reliable outcomes).

Result Presentation: (Visualization of the analyzed outcomes on a dashboard, furnishing actionable insights and recommendations for potential interventions or course corrections.

Development of a Python-based Software Tool:

Library Imports: (Importation of essential modules and libraries for optimal functionality; NumPy for array manipulation; Scikit-Fuzzy for fuzzy logic implementation; Matplotlib for graphical visualization)

Declaration of Input Variables: (Identification and declaration of five input variables, encompassing biometrics, facial expressions, vocal tone, textual commands, and motion; The scope of each variable is defined within a range of 0 to 100).

Declaration of Output Variable: (Establishment of a single output variable termed "danger level," with a value spectrum ranging from 0 to 100).

Fuzzy Sets Construction: (Automated generation of fuzzy sets for the declared input and output variables, providing a nuanced context for analysis).

Rule Declaration: (Development of fuzzy rules for the control system, thereby guiding the system's behavior; For instance, a "poor" biometric reading correlate to a "very low" danger level).

Fuzzy Control System Creation: (Consolidation of the defined fuzzy rules into a singular fuzzy control system architecture).

Simulation: (Initialization of a simulation object predicated on the established fuzzy control system, aimed at prospective validation and analysis).

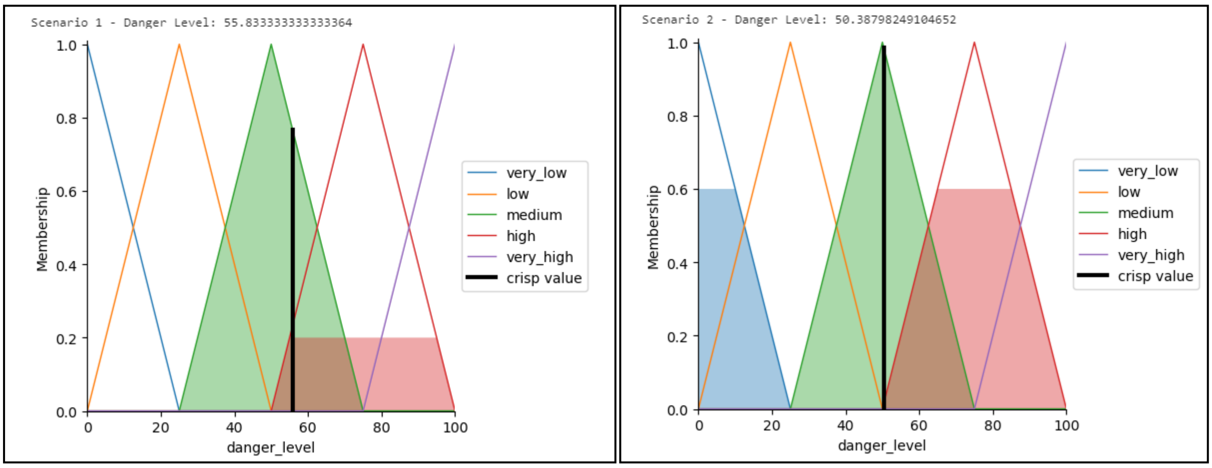
Testing Scenarios: (Pronouncement of an array of test scenarios, each equipped with predetermined input values for rigorous evaluation).

Result Output: (Iterative cycling through each testing scenario; Calculation of the danger level for each scenario; Console-based output for immediate review).

Graphical Visualization: (Comprehensive graphical illustration of fuzzy sets and resultant values for enhanced interpretability).

Legend Placement: (Strategic positioning of the legend on the plot to avoid overlapping with data lines).

Graph Display: (Invocation of plt.show() function for the real-time presentation of plots).



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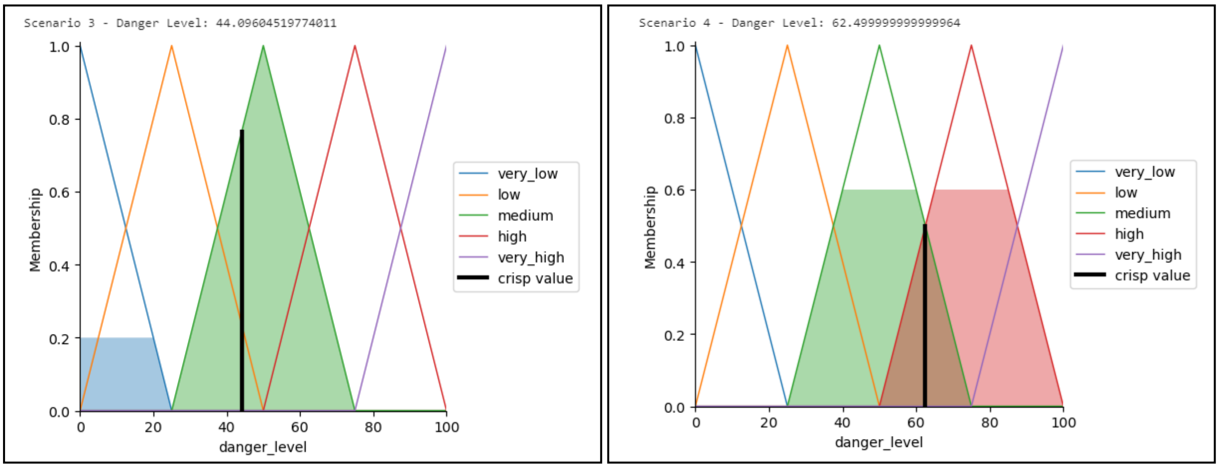

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Figure 1: Graphical visualization of crew danger levels post-intelligent biometric analysis prior to ship berthing

The graphs delineate the danger levels across various scenarios based on five input variables: biometrics, facial expressions, vocal tone, textual commands, and motion.

X-Axis: Represents the magnitude of input variables and the output variable, termed "danger_level," within a specified range of 0 to 100.

Y-Axis: Depicts the degree of membership to assorted fuzzy categories, for example, 'very_low,' 'low,' 'medium,' 'high,' and 'very_high' concerning the danger level.

Interpretation of Graphs:

Scenario 1: With biometrics at 50, facial expressions at 70, vocal tone at 40, textual commands at 30, and motion at 80, the danger level may skew higher due to elevated levels of motion and facial expressions.

Scenario 2: Given low biometric and facial expression indicators but a high vocal tone, the danger level may manifest as moderate.

Scenario 3: With a high biometric reading but a low motion score, the result may yield a moderate danger level.

Scenario 4: With elevated levels across most parameters, the danger level is likely to be high.

The visualizations serve as an instrumental tool for elucidating how various combinations of input variables impact the danger level. Such insights are invaluable for security systems that necessitate rapid risk assessments based on an array of contributing factors.

Conclusion. Practical Implications of the Software Application in Port Operations.

Multifactorial Assessment: The program facilitates the simultaneous evaluation of multiple parameters—biometrics, facial expressions, vocal tone, textual commands, and motion—thereby enhancing the accuracy of danger level assessments.

Adaptability: The utilization of fuzzy logic accommodates the inherent ambiguities or uncertainties, rendering the system more adaptive to real-world conditions.

Response Time: The software is capable of rapidly processing input data and delivering real-time conclusions, a feature that is critically important in port operations where immediate response to threats is imperative.

Modularity: The ease of making modifications or adding new parameters/rules makes it possible to tailor the system to meet the specific needs of the port.

Decision-making Flexibility: The system can accommodate various degrees of decision levels, ranging from "very low" to "very high" danger levels, thereby allowing port operators to manage security resources flexibly.

Data Visualization: Graphs and charts enable operators to clearly comprehend how input variables influence danger level assessments and can serve as a convenient tool for analysis and planning.

Human Error Minimization: Automating the danger assessment process mitigates the potential for error or subjectivity in evaluations made by personnel.

Security Enhancement: Through precise and quick analysis of danger levels, the software aids in the timely identification of potential threats, leading to an overall improvement in the safety standards within the port zone.

In summary, the proposed approach holds significant promise as an instrumental tool for optimizing safety and efficiency in port operations.

List of References

1. Nosov P., Ben A., Safonova A., Palamarchuk I. (2019) Approaches going to determination periods of the human factor of navigators during supernumerary situations // Radio Electronics, Computer Science, Control № 2(49). - 2019. Pages 140-150. https://doi.org/10.15588/1607-3274-2019-2-15. [in English]

2. Zinchenko Serhii, Tovstokoryi Oleh, Nosov Pavlo, Popovych Ihor & Kyrychenko Kostiantyn (2023) Pivot Point position determination and its use for manoeuvring a vessel, Ships and Offshore Structures, 18:3, 358-364, https://doi.org/10.1080/17445302.2022.2052480. [in English]

3. Nosov P., Krapyvko G., Ben A., Safonov M., Zinchenko S. (2019) Disabling the dynamic positioning of the vessel as a cause of the negative influence of human factor in maritime transport. МНПК пам'яті професорів Фоміна Ю. Я. і Семенова В. С. (FS - 2019), 24 – 28 квітня 2019, Одеса – Стамбул – Одеса. Pages 309-315[in English]

4. Heikkilä, Marikka, Jouni Saarni, and Antti Saurama. (2022). "Innovation in Smart Ports: Future Directions of Digitalization in Container Ports" Journal of Marine Science and Engineering 10, no. 12: 1925. https://doi.org/10.3390/jmse10121925. [in English]

5. Blokus, A., Dziula, P. (2019) Safety Analysis of Interdependent Critical Infrastructure Networks. TransNav, the International Journal on Marine Navigation and Safety of Sea Transportation. 13, 4, 781–787 (2019). https://doi.org/10.12716/1001.13.04.10. [in English]

6. Popovych, Ihor & Shcherbak, Tetiana & Kuzikova, Svitlana & Blynova, Olena & Nosov, Pavlo & Zinchenko, s. (2021). Operationalization of tactical thinking of football players by main game roles. Journal of Physical Education and Sport. 21. 2480-2491. https://doi.org/10.7752/jpes.2021.05334. [in English]

7. Ihor Popovych, Ihor Halian, Olena halian, Pavlo Nosov, Serhii Zinchenko, Vitalii Panok. Research on personality determinants of athletes' mental exhaustion

during the ongoing COVID-19 pandemic. Journal of Physical Education and Sport, 2021, 21(4), стр. 1769–1780, 224. [in English]

8. Hornauer, S., Hahn, A., Blaich, M., Reuter, J.: Trajectory Planning with Negotiation for Maritime Collision Avoidance. TransNav, the International Journal on Marine Navigation and Safety of Sea Transportation. 9, 3, 335–341 (2015). https://doi.org/10.12716/1001.09.03.05. [in English]

9. Solovey, O., Ben, A., Dudchenko, S., Nosov, P. (2020). Development of control model for loading operations on Heavy Lift vessels based on inverse algorithm. Eastern European Journal of Enterprise Technologies, 5/2 (107), 48–56. https://doi.org/10.15587/1729-4061.2020.214856. [in English]

ДЕРЖАВНЕ РЕГУЛЮВАННЯ ЛАНЦЮГА ПОСТАВОК ЗАМКНУТОГО ЦИКЛУ В КОНЦЕПЦІЇ ЦИРКУЛЯРНОЇ ЕКОНОМІКИ

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Анотація. Сьогодні країни стикнулися з низкою проблем, які привернули увагу політиків, бізнесу, громадськості та наукової спільноти і поставили під питання доцільність традиційної моделі економіки та висунули на порядок денний концепцію циркулярної економіки. Державне регулювання ланцюга поставок замкнутого циклу, також відомого як циркулярна економіка, включає в себе використання ресурсів у зрециклльованому або вторинному вигляді, замість постійного використання нових сировинних матеріалів. Державне регулювання може бути доцільним для прискорення