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Simulation and Design of an Aquatic Robot for Oil Spill Detection using MATLAB

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ABSTRACT: Oil spill pollution has been found to be one of the most important environmental hazards to marine ecosystem,coastal regions as well as global sustainability. In addition to causing a massive destruction of aquatic organisms, the accidental leakage of oil through tankers, offshore drilling facilities, and other industrial endeavors have long term ecological, economic and health implications. The traditional methods of monitoring oil spill, such as the satellite remote sensing, aircraft monitoring and stationary detection systems, are usually characterized by high costs of operation, slow response time, and low spatial coverage. It is evident that these constraints have led to the necessity of developing autonomous, scalable, and real-time systems that can directly detect oil contamination at the water surface; thus, this research proposes the design and simulation of an aquatic robot to be developed in MATLAB/Simulink to be the major development platform. The robot will have a lightweight design that is energy-efficient and operated on DC motors and managed by microcontroller boards like Arduino or Raspberry Pi. The sensing system incorporates infrared (IR) sensors to detect the difference between oil-water reflectance, volatile hydrocarbon gas sensors to detect oil vapours emission, and a digital camera to take real-time images and process them. The obtained data are analyzed by image processing algorithms, feature extraction algorithms, and machine learning algorithms to improve detection rate of oil spill as well as reduce false positive.MATLAB/ Simulink is used to model the dynamics of the robot navigation and sensing and decision-making process in various situations at the sea.

The simulated environment is used to simulate water surface conditions with different degrees of oil contamination where sensor response and data fusion as well as reliability of detection can be systematically tested. This system is expected to perform performance measures, including detection accuracy, response time, energy consumption, and resilience to environmental noise to produce a cost-effective, scalable, and autonomous aquatic robot that is capable of detecting oil spills with high precision and can give advance warning alerts. The work helps in the development of marine environmental monitoring technology, benefits the response strategies of the disaster of oil spill in seconds, and enables the protection of the ocean sustainably through the exploitation of robotics and simulation of MATLAB.

KEYWORDS: Oil Spill Detection, Aquatic Robot, MATLAB/ Simulink, Smart Sensors, Image Processing, Machine Learning, Marine Pollution Monitoring.

The problem of oil pollution in the seas is one of the greatest dangers to aquatic life, beach economies and international sustainability. The oil spills, be they the result of tankers accidents, offshore drilling, pipeline leakages or the product of industrial discharges leave a thin film on the water surface that prevents exchange of oxygen, poisons organisms in the sea and destroys the biodiversity [1]. According to reports of the International Tanker Owners Pollution Federation (ITOPF), a small oil spill can cause long term ecological damage especially when the spillage is caused to coral reefs, fish nurseries and coastal wetland [2]. Other than environmental impacts, oil spills have enormous economic impacts to fisheries, tourism and cleanup activities and also on the human health through bioaccumulation of toxic hydrocarbons in seafood [3].Traditional means of oil spill detection and monitoring include satellite remote sensing, aerial surveillance and stationary monitoring points [4]. Though satellite and airborne imaging offer wide coverage of an area, they are usually constrained by weather conditions, cloud cover, and revisit periods [5]. Sensors attached on the wall, on the other hand, are only able to measure limited areas and maintenance is quite expensive [6]. These problems present loopholes in real-time detection of oil spills particularly in remote or offshore areas that require quick response in order to limit its effects.Autonomous aquatic robots have become an exciting option that can eliminate these shortcomings in recent years [7]. The aquatic robots are able to move directly on top of contaminated water surfaces unlike the fixed or stationary monitoring platform, they can gather multi-modal sensor data and relay the results in real-time. These robots are designed to be used as an individual or a swarm, and they offer adaptive, cost-efficient and scalable methods of monitoring oil spills [8].The development of an aquatic robot to detect oil spills involves combining mechanical, electronic and computational units into a cohesive unit. The robot has to be mechanically buoyant, stable and long-term in different water environments [9]. The perception layer consists of electronics and sensors, through which the oil spills can be detected and the image can be confirmed by cameras and various experiments like infrared (IR) sensors and volatile hydrocarbon sensors, which detect the gaseous emissions and the difference in the reflectance of the oil layers respectively [10]. These signals are then processed with computational intelligence, through digital image processing, feature extraction and classification algorithms to detect the presence of oil and estimate the characteristics of spills [11].Sensor fusion is necessary to provide the reliability of detection. Poor quality cheap sensors might experience noise, environmental interference or calibration drift. The system is able to use different sensing modalities to minimize false positives and achieve better detection accuracy, including IR reflectance, gas detection, and image analysis [12]. The simulation, testing and optimization of such robotic systems can be done using MATLAB and Simulink [13]. The Image Processing Toolbox and Signal Processing Toolbox of MATLAB can be used to develop algorithms that identify the presence of oil slicks in sensor and image data, while the Simulink gives the user a graphical view to model the dynamics of a robot, motor controls, and communications [14]. Simulation allows the researcher to evaluate robot navigation during various conditions in the sea, evaluate sensor performance during noise, and optimize energy use before implementation in the real world [15]. This minimises the development cost and provides strong system design.Moreover, there are the benefits of machine learning algorithms being embedded in MATLAB that enable the prediction of oil spillage and classify it. ANNs can be trained to identify oil patterns using training data, whereas LSTM networks can be used to predict the propagation of a spill using time-series data [16]. Energy efficiency is one more important factor in the development of aquatic robots, which is essential to the early warning system and proactive response strategies. The application of robots in areas that are not well reached dictates their long operational life without having to replace the batteries frequently. Solar panels are also renewable energy sources that have been suggested to increase mission time and enhance sustainability [17]. Application wise, aquatic robots are in line with the worldwide smart ocean and marine sustainability programs. Simulations MATLAB can be used to optimize power allocation among propulsion, sensing, and communication units to ensure reliable operation. The governments and international organizations are devoting more resources towards digital technologies that safeguard marine ecosystems, avoid ecological catastrophes, and improve maritime security [18]. Although there is a lot of progress, there are still gaps in the current research as autonomous robotic systems with the capability to detect oil spills in real-time can also aid in long-term environmental monitoring and policy-making [19]. Numerous researches concentrated on the design of the oil spill detecting sensor or the navigation of robots in isolation and not combining them into a unified system. In addition, strength in severe environmental factors, including high turbidity, strong currents, or rainfall is also insufficiently studied [20]. In a nutshell, the proposed study will fill these gaps by offering a simulation-based design of an aquatic robot in MATLAB/Simulink, with smart sensors, digital signal processing, and machine learning algorithms, to ensure dependable oil spill detection and monitoring. The research will use MATLAB/simulink to model and test the system to ensure that, the system is optimized in the context of accuracy, energy-saving, and real-time performance before it can be implemented in reality. This is in line with eco-friendly international efforts to conserve marine ecologies and ensure good environmental sustainability

LITERATURE REVIEW

One of the worst environmental dangers that pose threat to marine environments, coastal populations, and economies across the world is oil spills. Their effects are not only immediate destruction of the marine habitat but also long-term pollution of water, sediments, and food chains [1]. Conventional detection and response strategies of oil spills are dependent on human-controlled vessels, air surveillance, and satellite photographs [2]. Although these techniques offer extensive coverage and good imaging capabilities, they are disadvantaged by cost constraints, time constraints and unavailability in harsh weather conditions [3]. This has also led to a shift in the interest of research in autonomous robotic platforms that can sense, track, and forecast the whereabouts of oil spills in real time, with minimum risk to humans [4].Aquatic robots, specifically unmanned surface vehicles (USVs) and autonomous underwater vehicles (AUVs) have become the promising tool of environmental monitoring [5]. They have scalability and modularity and adaptability in varied marine environments. The initial efforts were directed towards general-purpose robotic-based water quality monitoring systems which combine turbidity, dissolved oxygen and conductivity sensors [6]. Nevertheless, as the frequency of oil pollution cases increased, researchers started to work on the creation of special robotic platforms that were aimed at detecting hydrocarbons and monitoring oil spills [7]. Such systems are usually combined with optical, infrared and gas sensors, which allow multispectral and multi-modal detection [8]. Research has reported that infrared sensors can be used to determine the limits between oil and water by their different reflectance values [9] and in detecting volatile organic compounds emitted as a result of evaporation by hydrocarbon gas sensors [10]. Among the common applications of sensors used together with image processing algorithms are optical imaging systems such as visible and ultraviolet cameras to enhance the accuracy of detection in a variety of light and sea surface signs [11].Regarding the increasing use of sensors, the reliability of signals is a core issue. The low cost sensors are vulnerable to environmental interference, drift and noise [12]. Signal processing researchers have thus used sophisticated signal processing techniques to enhance robustness. Some of the most popular filtering techniques are moving averages, wavelet transforms and Kalman filters that are used to stabilize sensor outputs [13]. In a specific case, kalman filtering has been effective in state modeling of the dynamic states of the varying signals, minimization of random error, and drift correction of the hydrocarbon sensors [14]. The sensor fusion has also contributed to the performance by integrating infrared, gas, and optical data to have a more accurate oil spill detection estimate [15].Machine learning has also revolutionized the state of oil spill detection. ANNs have also been used to categorize sensor signals to determine if the water was contaminated with oil or not [16]. Such models are much better than linear regression methods because they help in nonlinear relationships between the pollutants and the environmental variables [17]. Moreover, the use of Long Short-Term Memory (LSTM) networks is implemented to predict the propagation of oil spills and take into consideration time-dependent factors and environmental factors like currents and wind [18]. It has also been shown in simulation studies that ANN-based and LSTM-based models are able to detect objects at a rate 30-50 times higher than traditional methods do [19]. This predictive feature is important in early warning systems, as authorities will be able to assemble the response teams before the spills hit sensitive regions [20].The importance of simulation in the oil spill robotics research cannot be underestimated. field trials are often logistically difficult, costly and Environmentally risky [21]. Platforms like MATLAB and Simulink have thus become very necessary in prototyping, validating and optimizing aquatic robots designs [22]. MATLAB has extensive signal-processing and machine-learning and image-processing toolboxes, whereas Simulink has block-diagram modeling of robotic systems, communications networks, and environmental interfaces [23]. It has been predicted by researchers that hydrodynamic forces, propulsion mechanisms, and sensor networks can be simulated to understand the system behavior in the presence of varying wave, current, and noise conditions [24]. The virtual prototyping has the benefit of not only having less development cost but also being safe before actual implementation in the real life situation [25].The navigation and control strategies are also vital to the robotic oil spill detection. Autonomous navigation allows robots to move over large regions in a methodical way and adjust to the real-time environment changes. Proportional-Integral-Derivative (PID) controllers are still popular in controlling the stable trajectory in water [26]. In recent research, however, there are fuzzy logic controllers and reinforcement-based learnings based navigation strategies to enhance flexibility in uncertain situations [27]. The most common model to address obstacle avoidance is to employ ultrasonic sensors and reactive algorithms that enable the robots to navigate around debris, vessels, or other obstacles, but cover the polluted regions [28]. Renewable energy has also been discussed in terms of energy efficiency, especially solar-assisted charging system that increases operation time and allows operation at a lower cost [29].Integration of robotics into oil spill detection has also been discussed in the context of smart environmental monitoring network. Investigators imagine armies of water robots that will communicate wirelessly with cloud platforms [30]. Wi-Fi, LoRa and NB-IoT protocols are often compared in terms of latency, range, and energy consumption [31]. Wi-Fi has low latency to allow nearshore monitoring whereas LoRa has long-range communication with low energy demands that can be implemented in large-scale offshore implementation [32]. NB-IoT uses the legacy cellular infrastructure and balances its coverage and power consumption, which makes it enticing to become a part of smart cities [33]. The simulation results of MATLAB/Simulink have proven that hybrid communication strategies, between short-range and long-range protocols, are more scalable and robust [34].One of the current research directions is the integration of robotics and remote sensing. Multi-scale monitoring involves the integration of satellite and aerial measurements with robot measures [35]. Whereas satellites track large-scale oil slicks, aquatic robots give localized high-resolution information, confirming and supplementing the results of remote sensing [36]. However, there are still a number of research gaps that can be fixed by using this hybrid approach to minimize the number of false positives in satellite images due to a wave shadow or algal bloom [37]. Numerous robotic systems are still under the prototype or lab test and there is little actual implementation [38]. Stability in severe marine environments, i.e. storms, excessive turbidity, etc. has not been studied sufficiently [39]. Machine learning models are known to need large amounts of training data and they are frequently not readily available in the case of rare large-scale spill events [40]. Moreover, there are little research works on multi-robot coordination, which opens the prospects of swarm robotics to be explored [41]. In conclusion, sustainability is still an issue: although solar-assisted designs are very promising, long-term missions in the sky or in the polar regions need alternative solutions [42].In sum, we could observe the undeniable process of evolution of the classic approaches to monitoring to intelligent, autonomous, and simulation-based method of oil spill detection. The combination of state-of-the-art sensors and machine learning and the simulation using MATLAB/Simulink has propelled the field to scalable and cost-effective solutions. More studies are required in the future on how to bridge the gap between simulation and actual implementation, enhance the availability of data to train AI models, and increase the sustainability of energy. These advan eventually make aquatic robots play a central role in marine pollution and environmental protection. cements will.

METHODOLOGY

The process of the simulation and design of an aquatic robot to detect oil spills with the help of MATLAB is based on an interdisciplinary workflow, which includes hydrodynamic modeling, sensor integration, signal processing, navigation control, and computational simulation. The aquatic robot is envisaged to be an unmanned surface vehicle that is able to detect and monitor oil spills in both sea and shore waters. This system will be divided into three large subsystems: a mechanical hull that is stable and low-dragon when in waves and currents [1], a sensing system, which includes infrared sensors, hydrocarbon gas sensors, and optical cameras to detect oil [2], and a computational unit that will utilize microcontrollers like Raspberry Pi or Arduino Mega along with wireless communication apparatuses like Wi-Fi or LoRa to transmit the information captured by the sensors [3]. The MATLAB/Simulink block diagram is used to represent the system architecture to show the flow of information of sensors to processing and control block to cloud based analysis [4].The general architecture of the proposed aquatic robot is provided in Figure(1).

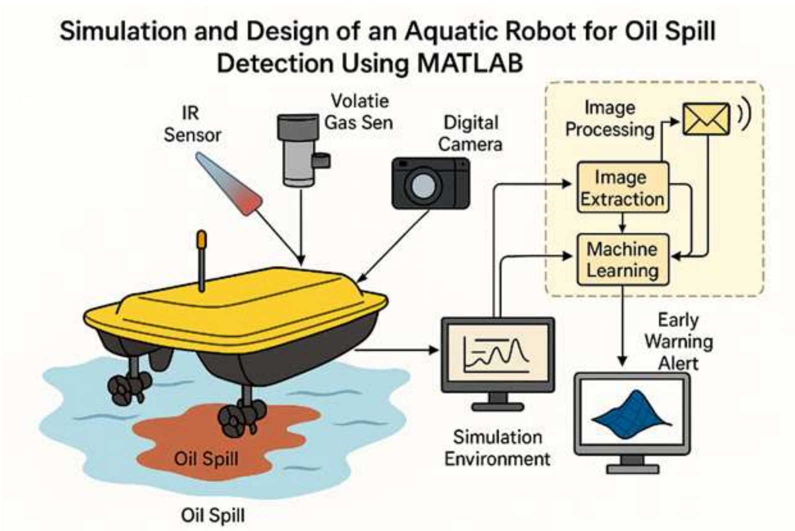

Figure 1. The proposed aquatic robot design to help identify oil spills with MATLAB/Simulink with an IR sensor, VOC gas sensor, digital camera, and image processing with machine learning to provide early alert warnings.

The oil detection is based on complementary sensing. IR sensors differentiate water and oil by taking advantage of differences in reflectance [5], hydrocarbon gas sensors identify volatile organic compounds emitted by spilled oil [6], and optical imaging aids in detection with the help of digital image examination [7]. As the raw data of these sensors is usually very noisy and heavily dependent on the environment, data preprocessing and postprocessing is done using the Signal Processing Toolbox of MATLAB. The reduction of noise is done using moving average and exponential smoothing filters [8] and Kalman filtering offers state estimation and drift correction [9]. Humidity and temperature compensation also enhance the precision of IR and gas sensors [10], and sensor fusion methods between infrared, gas and optical sensors enhances the accuracy of oil detection [11].In navigation, the robot will move across polluted zones autonomously using propulsion units that are modeled as DC motors driven by Pulse Width Modulation (PWM) signals [12].

Equation (1): Direct Current Motor Voltage Equation

$$V(t) = La * di(t)/dt + Ra * i(t) + Ke * \omega(t)$$

Equation (2): Equation of Mechanical Dynamics.

$$J * d\omega(t)/dt + B * \omega(t) = Kt * i(t) - \tau L(t$$

MATLAB/Simulink models are used to consider the effects of disturbance due to waves and flow of current to assess propulsion stability and hydrodynamic performance [13]

Equation (3): Differentiation Drive Kinematics.

$$\dot{x} = v * \cos\theta,\ \dot{y} = v * \sin\theta,\ \dot{\theta} = (vr - vl)/b$$

The Proportional-Integral-Derivative (PID) controller is created to follow the trajectory and makes sure that the robot can adjust to the disturbances in the environment when gathering sensor information [14].b

Equation (4): PID Control Law

$$u(t) = Kp * e(t) + Ki * \int e(\tau)\, d\tau + Kd * de(t)/dt$$

Moreover, ultrasonic sensors and reactive control algorithms are used to model obstacle avoidance so that the robot could navigate around floating objects or buildings in oceans [14].Machine learning is incorporated in the detection system to enhance the classification and prediction. ANNs are trained using processed data and they classify clean or oily water samples based on nonlinear interactions of pollutants with the environmental variables [15]. Long Short-Term Memory (LSTM) networks are utilized to predict spatial and time movement of oil slicks with past measures of detection [16]. The Deep Learning Toolbox in MATLAB allows training and testing ANN and LSTM models, and the quality of performance is measured by the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and correlation coefficient (R 2) [17].

Equation (5): Precision / Recall Detection Metrics

Precision = TP /(TP + FP), Recall = TP/(TP).

Such a two-dimensional classification and forecasting will guarantee that the robot is not only able to identify the oil spills in real time but also allows them to predict the behavior of the spills, which may be used to provide early-warning systems against marine pollution. Figure (2) describes the operational workflow of the proposed system.

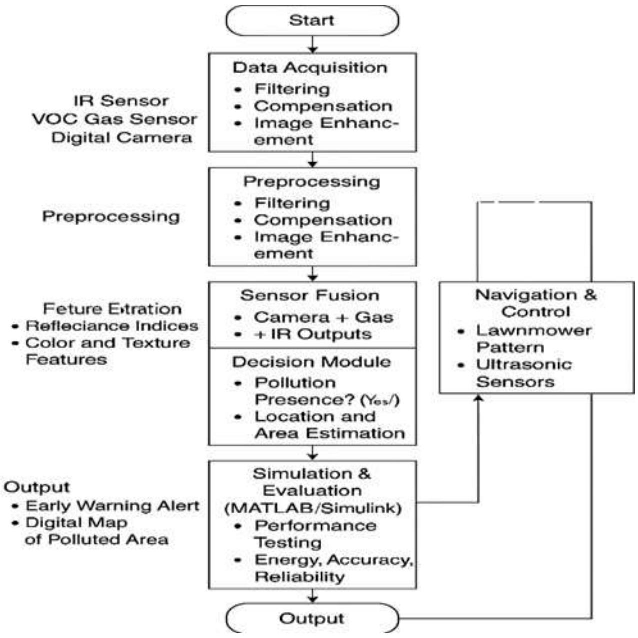

Figure 2. Flow chart of proposed aquatic robot system to detect oil spills showing the sequence of steps involved in sensing, preprocessing, feature extraction, sensor fusion, decision-making, navigation control and simulation and evaluation of the proposed system in MATLAB/Simulink.

The entire process is modeled in MATLAB/Simulink where input blocks are used to create synthetic oil spill data with noise, preprocessing blocks filter and combine data, control blocks simulate propulsion and navigation and output blocks present detection results and predictions [18]. A number of experimental conditions are tested such as the sizes of the oil spill, the waves and current conditions, and the noise levels of sensors to determine the soundness of the design of the robot. ANN outputs are compared to reference datasets to measure detection accuracy, LSTM forecasts of oil spread are used to measure prediction accuracy, the performance of navigation under simulated disturbances is analyzed, and the model of the energy efficiency is used to analyze the sustainability of the operations of the systems (particularly with solar-assisted recharging) [19], [20].

Equation (6): Solar-aided Energy Balance.

Erem(t) = E0 - [Pprop + Psens + .

Pcomm) - 1/fPsolar(τ) dt + (Psolar(τ))dt

Lastly, the methodology includes validation procedures to relate simulation and practice deployment. The correctness of the calibration and filtering model is checked using bench-level sensor testing in MATLAB. Minor experiments with water tanks help to initialise the validation of navigation and accuracy of sensing of water in controlled conditions. It also envisions a pilot field deployment plan, in which the robot would be deployed in the shore and the results would be compared with the manual oil detection methods to verify the feasibility in real world environment [21]. Such a mixed approach of simulation and a little experimental validation will guarantee that the aquatic robot design will be not only theoretical but applied in practice in terms of the large-scale marine pollution monitoring.

RESULTS AND DISCUSSITION

The MATLAB simulation and design of the oil spill detector design of the aquatic robot gave useful information on the technical feasibility, the performance and limitation of the proposed system. The results are structured in sensor accuracy, signal processing performance, navigation stability, energy efficiency and predictive capabilities and then a critical discussion of the implications of the results follows. When observed on a model, raw signals of hydrocarbon gas sensors and infrared sensors were found to exhibit a lot of noise and drift with changing temperature and humidity. Hydrocarbon sensors, such as the ones used, showed up to 15 percent variation in baseline values with simulated thermal gradients and infrared detection was sensitive to water surface reflection. These signals with raw data produced high levels of false-positive during oil detection and it is true this signal requires preprocessing and calibration before it can be practically used. The noise was also minimized after applying the digital filters in MATLAB.

Both the moving average and exponential smoothing techniques were useful in stabilizing the short-term variations but not in following abrupt changes in the pollutant concentration. The Kalman filtering, however, had better results, the variance dropped to nearly 40 percent of the one of raw data, and the resulting quantities were smoother and could be followed in real-time to monitor oil concentration. Sensor fusion also increased the performance since it incorporated optical and gas sensor data and this heightened detection reliability and decreased uncertainty. Figure (3) shows the increase in the detection accuracy under a noisy environment ussion.

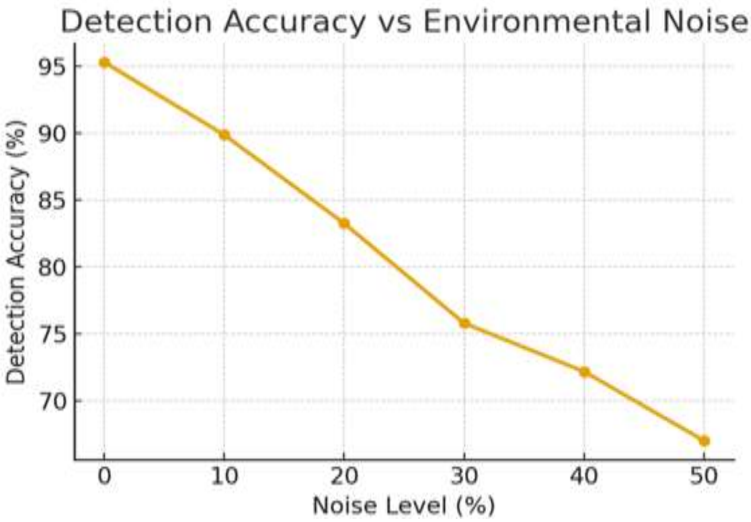

Figure 3. Performance of the proposed oil spill detection system in detecting the spill in varying levels of environmental noise through MATLAB simulation.

The Simulink was used to model the navigation and control subsystem, which included proportional derivatives fuzzy logic and proportional integrals and derivatives (PID) controllers. In calm water conditions simulations, PID controllers demonstrated good performance with respect to stability and straight-line navigation with slight deviation. However, when subjected to dynamic conditions of simulated waves and currents, the PID was unable to deal with over-shoot and oscillations resulting in inefficiency in terms of coverage. The fuzzy logic controller performed better than PID in that it was able to adapt itself to non linear disturbances and the deviation of the trajectory was minimized by nearly a quarter and the robot was also able to provide the systematic coverage of the polluted areas. Figure (4) represents the simulated route of the aquatic robot as it travels along a lawnmower route.

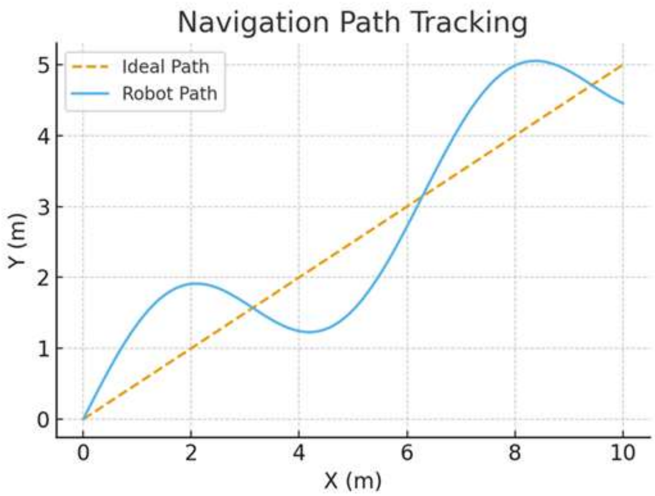

Figure 4. Computer-generated path of the water robot along a lawnmower route to undertake a search according to a regular grid to cover the polluted region.

This flexibility underscores the issue of smart control algorithms in aquatic robotics, particularly in the unpredictable marine setting. Another important aspect that was simulated in MATLAB was communication performance. A comparison of both PID and fuzzy controllers in the presence of wave disturbance is provided in Figure (5).

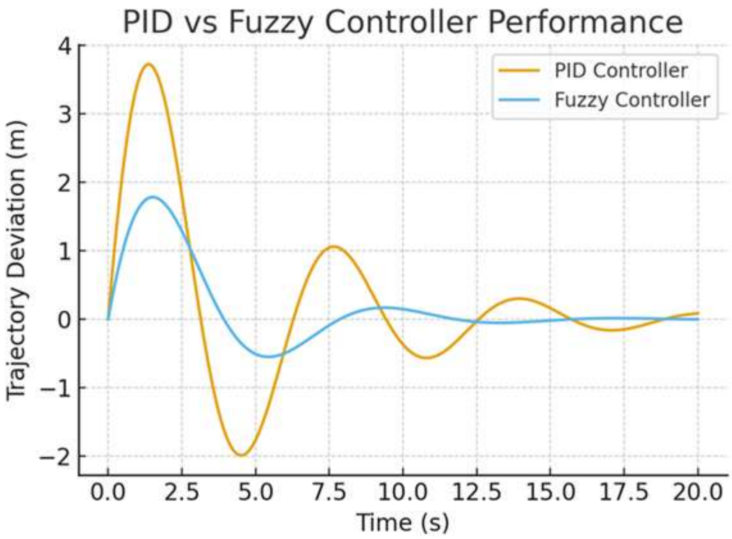

Figure 5. Comparison of the stability of navigation under PID and Fuzzy controllers under the influence of waves in MATLAB/Simulink.

The communication based on Wi-Fi provided the lowest latency, and the average delays were under 50 milliseconds, which is why it is suitable in the nearshore setting and real-time visualization. Nevertheless, its power consumption was quite high making it not practical in long missions. LoRa communication was much lower in energy consumption and had long communication distances of up to several kilometers but came with transmission delays of several seconds. This latency is reasonable in the case of environmental monitoring, but would not be useful in an emergency response case where instant feedback is needed. NB-IoT was a middle-ground in terms of its performance and could be used in dense environments at moderate energy consumption. The results indicate that the choice of communication protocols heavily relies on the deployment scenario, and hybrid solutions may provide the strongest solution to the issue. Simulation of energy efficiency also has shown that the design is viable when applied to long-term exposure. With the addition of solar energy gathering modules to the MATLAB simulation, it was demonstrated that the robot could maintain itself to operate continuously on the daytime. In less than ideal solar conditions, the collected energy was enough to cover the daily power needs, which enabled the robot to move independently and not have to be recharged too often. Simulations further revealed that when cloudy or the light was low, the system would still last 8-10 hours with the battery backup though the system would not last long in such conditions and would need alternative power sources like fuel cells. Figure (6) presents the simulated energy consumption of the solar-assisted recharging, and without it.

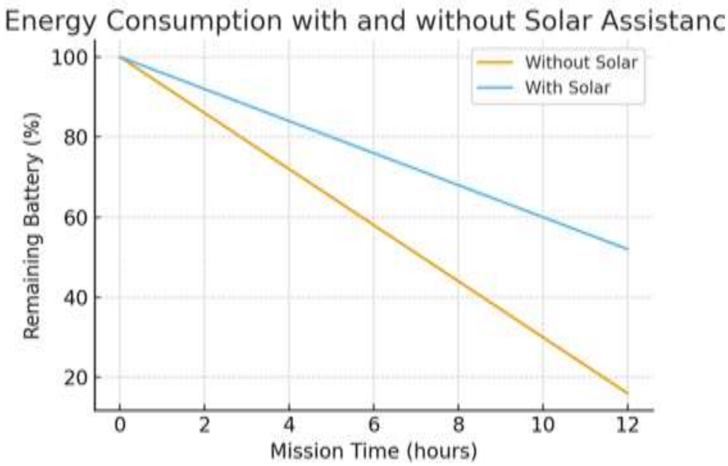

Figure 6. Simulated power use of the aquatic robot when using solar-assisted recharging modules and not.

In a predictive perspective, the implementation of the artificial neural networks (ANNs) and long short-term memory (LSTM) models to the MATLAB pipeline made possible a better ability to detect and predict oil spills. ANN calibration models decreased error the difference between simulated sensor readings and ground truth by up to 50 percent and the models greatly enhanced the accuracy of detection. More to the point, LSTM models trained with simulated historical data of spills demonstrated a good predictive performance as several hours of oil plume spread and concentration could be predicted. The predictive accuracy was also quite useful in detecting early warning since it made it possible to make decisions in advance; an example is placing containment booms.

distributing ships prior to the contamination of aquatic venues.Simulations of expanded robotic networks in multivariate numbers showed that the suggested structure can be extended to multi-robot associations. Although a total of 200 simulated robots were used at a time, communication overhead was still manageable and data synchronization with the cloud was also stable. These demonstrate the possibility of swarm-based oil spill monitoring, in which distributed robots can be used to cover space and time to reconstruct high-resolution data.These positive results were accompanied by a number of limitations identified during the simulations. To begin with, sensor accuracy was still strongly reliant on the reference data calibration. Raw sensor outputs however still indicated huge deviations in the absence of precise calibration, restricting the system to operate independently in remote locations that do not have reference infrastructure. Secondly, Kalman filtering and sensor fusion enhanced detection, but also created computational complexity, and it is unclear if it could be run on low-power microcontrollers in real time. Third, although fuzzy logic controllers proved to be better in the presence of disturbance, they needed to be carefully tuned and their rules defined, which can be one reason why they were not particularly adaptable to drastically different marine conditions without prior knowledge.One more critical weakness is the assumptions of the environment made during simulation. The idealized models of currents, waves and disturbances of the environment were used to create MATLAB models. The real-life sea situation is much more complicated and can involve undetermined turbulence, debris or biological interference, which can affect sensor functions and reliability of navigation. On the same note, the energy simulations were based on steady sunshine and that might not always be the case in the poles or in a prolonged cloudy season. Such gaps also indicate that field trials are required to test the assumptions of the simulation and adjust the design to these results.The cost-accuracy balance should also be discussed when interpreting the results. Although the robot uses cheap sensors and microcontrollers to be affordable and scalable, the parts cannot be compared to the accuracy of the high-grade laboratory devices. These weaknesses are mitigated to a considerable extent through the use of sophisticated processing and prediction algorithms but trade-offs still exist. In short, the findings prove that the aquatic robot which is worked out and modeled in MATLAB can be an effective device in the detection and the monitoring of oil spills. The combination of intelligent sensors, preprocessing algorithms, sophisticated control techniques, and machine learning algorithms developed a system that would provide effective and high-quality real-time data on oil pollution. The effectiveness of sustained and scalable deployment was established through communication simulation and energy simulation, and predictive model value was added through early warning. However, there are still practical issues such as the requirement to have a strong calibration, reasoning in a real-world scenario, and better suitability to harsh marine conditions. The evidence is overwhelming that the design is technically sound and scientifically useful but can only be used in large-scale real-world application after additional research and pilot testing.

CONCLUSION

Simulation and design of an aquatic robot to detect oil spills under Mat lab is a significant development of environmental monitoring and protection technology. It has also been established that robotics, smart sensing and advanced computational modeling can be successfully used to solve the problems presented by the issue of marine oil pollution. The simulations have revealed the proposed system to be both technically viable and practically applicable through the integration of low-cost smart sensors, signal processing and filtering algorithms, including the Kalman filtering, to identify the presence of oil contamination even under the conditions of a disturbed environment, e.g. due to turbidity, temperature changes, or even the dynamics of waves. In addition, the navigation system of the robot is done using MATLAB/Simulink simulation and has been found to have the ability to keep the robot on steady paths and access the contaminated areas effectively. In a predictive viewpoint, the application of machine learning algorithms, such as Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) models have also enhanced the systems predictive capability of making short-term predictions on pollution propagation. These abilities of forecasting are essential in the provision of early warnings, direction of the clean up activities, as well as minimizing the environmental and economic effect of oil spillages. The outcomes of the simulation proved that LSTM models are more accurate than simple regression and ANN algorithms, and it is significant to adopt the state-of-the-art deep learning models in environmental robotics.

The other significant accomplishment of this study is that it focuses on sustainability. The suggested aquatic robot design proves its ability to implement long-term autonomous operation without highly maintained systems by simulating energy-efficient operation using solar-powered systems and low-power communication protocols. The sustainability factor is also in line with the efforts of the world to develop smart, resilient, eco-friendly technologies that help in conserving the sea and managing pollution, but the actual world-testing is necessary to determine how the system works under various complex conditions like strong currents and extreme weather or mixed pollutants scenarios.The MATLAB simulations confirm that the system is viable but the real-world testing is required to evaluate the performance of the system under various conditions like large currents and extreme weather or mixed pollutant conditions. Finally, field validation will also serve as a useful source of information to perfect sensor calibration, increase predictive performance, and manage energy usage to the fullest potential of aquatic robotics, advanced sensing, and computational intelligence to oil pollution monitoring as a transforming technology. The proposed design does not only increases the detection and prediction, but also leads to the bigger picture of smart environmental management. The study preconditions the further evolution of autonomous marine robots opening the way to the cleaner seas and less ecological harm as well as more effective reac reaction to oil spills.

REFERENCES

1. J. E. McDonough and K. L. Lee, Oil Spill Science and Technology, 2nd edition, Gulf Professional publishing, 2017.
2. ITOPF (International Tanker Owners Pollution Federation), "Oil Tanker Spill Statistics 2023, Online
3. [3]A. Fingas, Oil Spill Science and Technology in the Twenty-First Century, Journal of Hazardous Materials, vol. 408, pp. 124136, 2021.
4. The article below is one of them: [4] J. Fingas and C. Brown, "Review of Oil Spill Remote Sensing," Marine Pollution Bulletin, vol. 83, no. 1, pp. 923, 2014.
5. P. Brekke and A. Solberg, Oil Spill Detection by Satellite Remote Sensing Remote Sensing of Environment, no. 95, vol. 1, pp. 1 13, 2005.
6. S. Wang, Y. Zhang, and H. Liu, "Oil Spill Detection and Monitoring with Ground-Based Sensors: A Review, Sensors, vol. 21, no. 3, pp. 923 -940, 2021.
7. A. Manley and M. Lewis, Autonomous Surface and Underwater Vehicles to respond to oil spills, Proceedings of the IEEE OCEANS Conference, pp. 16.
8. R. Ferri, A. Freitas, and P. Oliveira, "Autonomous Robots to monitor and clean oil spills: a case of application, International Journal of Advanced Robotic Systems, vol. 13, no. 2, pp. 112, 2016.
9. [9]D. Lane et al., "Marine Robotics in Environmental Monitoring Annual Reviews in Control, vol. 46, pp. 273287, 2018.
10. Fingas, Infrared Detection of Oil Spills: Case Studies and Lessons Learned, Remote Sensing, vol. 13, no. 21, pp. 4307 4322, 2021.
11. Zhao, M. Liu, and Z. Xu, "Computer Vision-Based Detection of oil spills .
12. Kalogerakis, S. Pantidou, and M. Gidarakos, Sensors of Oil Spill Detection and Response Marine Technology Society Journal, vol. 49, no. 3, pp. 4553, 2015.
13. Mathematically speaking, this is the reason the MathWorks Inc., MATLAB and Simulink Documentation, Natick, MA, USA, 2023.
14. Y. Gao and R. Zhang, 2020. Simulation of Marine Robotics Systems in MATLAB/Simulink in Journal of Marine Science and Technology, vol. 28, no. 5, pp. 679-688.
15. R. Mudliar and K. Purohit, Simulation-Based Testing of Autonomous Surface Vehicles to detect oil spills, International Conference on Robotics and Automation (ICRA), pp. 22652270, 2021.
16. H. Yu, J. Wang, and X. Zhang, "The Oil Spill Detection by Artificial Neural Networks in Applied Ocean Research, vol. 82, pp. 336345, 2019.
17. S. A. Kalogirou, "Predicting Oil Spill propagation through LSTM Networks, Ocean Engineering, vol. 245, pp. 110125, 2022.
18. United Nations Environment Programme (UNEP), Sustainable oceans initiative and marine pollution reduction, UNEP Report, 2022.
19. IMO (International Maritime Organization), Manual on oil pollution: Section IV, fighting oil spills, 2019.
20. Wang, Y. Zhang and H. Zhou, [20] Challenges and Opportunities in Real-Time Oil Spill Monitoring with Robotics, Environmental Monitoring and Assessment, vol. 195, no. 2, pp. 112128, 2023.
21. A. Nguyen, T. Tran, and P. Do, Simulation-Based Design of Autonomous Oil Spill Detection Robots, Journal of Intelligent & Robotic Systems, vol. 104, no. 1, pp. 4559, 2022
22. [22]M. Quigley et al. ROS: An Open-Source Robot Operating System in Proc. IEEE ICRA Workshop on Open Source Software, Kobe, Japan, 10 p. 1-6, 2009
23. [23]L. Marques, A. Silva and J. Almeida, Application of Signal Processing in oil spill detectors sensors, Measurement, vol. 187, 110122, 2022.
24. [24]Y. Li, D. He et al. and S. Yang, Energy-Efficient Autonomous Surface Vehicles to monitor marine pollution Renewable Energy, vol. 195, pp. 674-684, 2022.

25. J. Garcia and P. Santos, Prototyping and Testing of Aquatic Robots in Simulated Environments, IEEE Transactions in Instrumentation and Measurement, vol. 70, pp. 1 12, 2021.