

ENHANCING ENVIRONMENTAL PRESERVATION THROUGH AN IoT CUSTOM- BUILT MONITORING STATION

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The Danube Delta Biosphere Reserve is a highly complex and dynamic ecosystem, where monitoring air and water quality is challenging due to its vast area and continuously changing environmental conditions. Despite existing initiatives, few practical and operational monitoring solutions have been implemented. This paper presents a tailored monitoring system based on Internet of Things (IoT) technologies and artificial intelligence algorithms for forecasting key environmental parameters. The system is deployed on an electric aquatic reed-harvesting boat, enabling mobile and adaptive data acquisition. By integrating IoT and AI, the proposed solution ensures efficient data collection, transmission, and interoperability, supporting advanced environmental monitoring and contributing to the long-term preservation of the Danube Delta's biodiversity.

Keywords: IoT monitoring, Wireless sensors, Cloud computing, LSTM

1. Introduction

Beginning in 2015, the Sustainable Development Goals report has monitored progress toward 17 interconnected objectives aimed at promoting peace and prosperity for people and the planet. These goals call for global partnership and action, while Sustainable Development Goals 13, 14, and 15 focus on combating climate change, conserving oceans and marine resources, and protecting terrestrial

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ecosystems, emphasizing the need for concrete actions to preserve the Danube Delta biosphere [1]. In 2020, the European Commission prioritized the European Green Deal, reaffirming its commitment to addressing climate and environmental challenges under the “do no harm” principle. Acting as both a roadmap and a growth strategy, the Green Deal aims to build a green, digital, inclusive, and resilient economy and to transform the EU into a competitive, net-zero economy by 2050, decoupling economic growth from resource use [2].

These European policies are particularly relevant for the Danube Delta, a UNESCO World Heritage site and one of the most diverse biosphere reserves worldwide, hosting over 5,500 species and comprising more than 20 strictly protected areas covering over 50,000 hectares, approximately 9% of the total reserve area [3]. Preserving such a fragile ecosystem requires a robust legal and institutional framework. Since the 1970s, the European Union has developed successive Environment Action Programmes, with the current eighth programme aligned with the European Green Deal. In parallel, the EU Biodiversity Strategy for 2030, adopted in 2020, establishes an ambitious framework for safeguarding nature and restoring ecosystems, grounded in key legislative instruments such as the Birds Directive 2009/147/EC, the Habitats Directive 92/43/EEC, Regulation No 1143/2014 on Invasive Alien Species, and EU Wildlife Trade Regulations No 338/97 [4]. The Habitats Directive requires Member States to maintain or restore endangered, vulnerable, or endemic habitats and species [5].

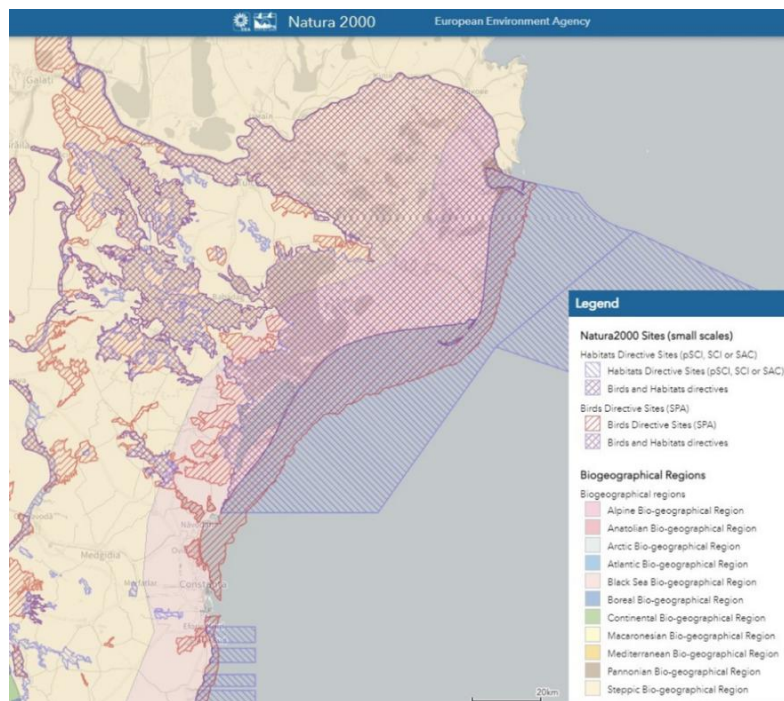


Fig. 1. Natura 2000 sites – Danube Delta.

At basin and national levels, institutions such as the International Commission for the Protection of the Danube River coordinate sustainable water management, pollution control, and ecosystem protection through policies and measures aimed at improving water quality [6]. In Romania, Government Decision no. 763/2015, approving the Management Plan of the Danube Delta Biosphere Reserve, defines key objectives including halting biodiversity loss, restoring ecosystem health, ecological reconstruction, and the development of integrated monitoring systems. However, despite this ambitious framework, few functional solutions or pilot projects have been implemented. Monitoring air and water quality remains challenging due to the scale, complexity, and dynamic conditions of the ecosystem, as well as persistent hardware and software integration issues.

In this context, Internet of Things–based digital solutions offer a promising approach. This paper proposes a customized IoT monitoring system deployed on an electric aquatic reed harvester boat operating in Natura 2000 protected areas, supported by artificial intelligence algorithms for predicting air and water quality parameters, and aims to contribute to the objectives of the EU nature restoration plan through practical and effective actions [7].

2. Literature review

Environmental monitoring is a widely debated topic in scientific literature, with studies focusing either on software or hardware solutions, or on integrated systems addressing data processing, prediction, and visualization. In recent years, there has been increasing interest in Internet of Things (IoT)–based environmental monitoring tools due to their low power consumption, ease of data transfer, cloud integration, and accessible data handling. This work focuses on state-of-the-art case studies and complementary research adopting a top-to-bottom approach, where smart sensors are connected to cloud platforms with visualization and AI processing capabilities. Most reviewed studies emphasize performance characteristics and the representation of monitoring data.

Several representative solutions highlight these trends. Paithankar et al. [8] proposed low-power portable sensors that transfer real-time air quality data (PM_{2.5}, PM₁₀, AQI) via IoT to a cloud platform, enabling pattern identification and long-term analysis. Shanmuganathan et al. [9] addressed anomaly detection using Markov- and LSTM-based networks, employing DHT sensors and NodeMCU for temperature and humidity monitoring, achieving high anomaly detection rates. Another case study in precision agriculture and ecological monitoring [10] used the ThingSpeak IoT platform, leveraging MATLAB integration for monitoring weather, soil, and water parameters with variable time steps. The availability of highly customizable solutions, including platforms supporting Python and R for

data storage and processing, reflects the maturity of digital technologies and encourages personalized monitoring architectures.

A broader perspective on existing technologies is essential during system design. Chamara et al. [11] reviewed the evolution of Ag-IoT systems between 2011 and 2021, showing that Arduino is the most commonly used hardware platform, while WiFi and LoRa dominate communication technologies. Cloud services such as ThingSpeak, Ubidots, Microsoft Azure, and custom-built solutions are most frequently adopted, highlighting the influence of project scale and researcher expertise. In parallel, Domínguez-Bolaño et al. [12] analyzed open-source IoT platforms, identifying widely used databases, integration tools, and visualization solutions, and emphasizing the diversity and functional differences among open-source approaches. Research specifically targeting the Danube Delta remains limited. Guttler et al. [13] analyzed turbidity gradients using satellite imagery and in-situ measurements, revealing seasonal and spatial variability, while Damian et al. [14] assessed socio-ecological vulnerability to multi-hazards such as drought and flooding. Overall, the reviewed literature indicates a clear need for concrete, tailored monitoring solutions to better understand and support the preservation of the Danube Delta biosphere.

3. Methodology behind IoT monitoring and AI tools

Based on the reviewed literature, the main aspect to consider at the beginning of the design stage was the mapping of the IoT concept on a case study and consideration of several pivotal factors, including but not limited to efficient power management, the accuracy of sensors, quantifiable elements to monitor, data transfer medium, communication protocols, resolution determination, data formats, integration tools, storage software, visualization tools, interoperability with other solutions and tools for data processing [15].

The process of aligning hardware and software monitoring solutions with the IoT paradigm involves the development of abstract layers, which represents a critical aspect of the implementation stage. The following figure, Fig. 2, presents an abstract representation of the implemented IoT concept.

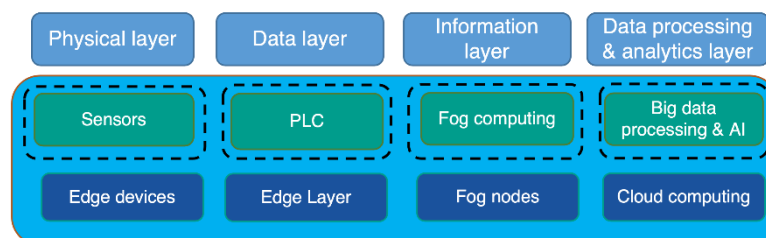


Fig. 2. Visual representation of the IoT concept for the case study

On the first layer, the Physical layer, the proposed solution is comprised of water and air quality sensors that have been integrated into the final monitoring solution. These sensors are connected to the solution either through wired connections or by means of Printed Circuit Board (PCB) technology. The accuracy of these sensors is presented in section 6. The Data layer consists of custom-built devices which are able to process, temporarily store and transfer the data to the next layer.

The third layer, the Information layer, is comprised of intermediary nodes which collect the data from, provide storage, and offer communication and transfer services to third-party applications or other layers of processing. On the last layer, the Data processing & analytics layer lies the software infrastructure composed of databases, processing, and visualization tools. Moreover, the fourth layer provides the efficient exchange of data with other applications of complex cloud-based solutions. Concerning the integration aspects of the proposed solution, the current case study has used two separate solutions for water and air quality monitoring. While both solutions align with the proposed Internet of Things (IoT) concept, they differ in terms of their communication protocols. Being a remote station, the data from both air quality and water monitoring stations are sent via a 4G modem. Both monitoring stations upload the data on the vendor's server, and it is afterwards retrieved and stored on a local IoT cloud platform.

4. Designing of the Reed Harvester

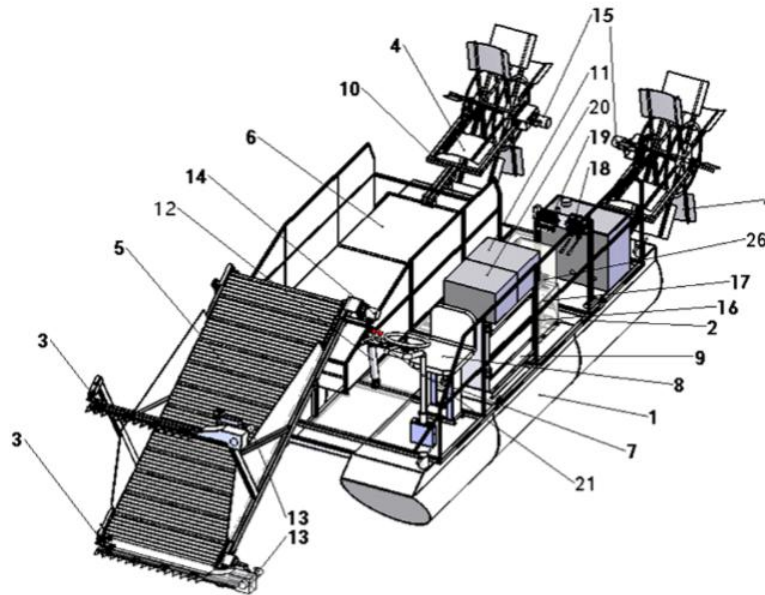
The self-propelled Reed Harvester Experimental Model (ERBA), as depicted in Fig. 3 is designed for use in rivers, reservoirs, lakes, canals and coasts. Besides performing the basic operations such as collecting the reed, the boat is used as infrastructure for the water and air monitoring system in the area where this data acquisition is needed. The electric boat is environmentally friendly by using an electrical motor of 14.5 kW and 33 kWh energy batteries. It realizes multiple tasks such as environmental IoT monitoring, cutting, collecting, storing and transporting reed or other waterweeds. The machine is driven by two paddle wheels instead of the screw propeller, which can make assure the wheel is not entangled by underwater weeds.

Its operating principle is the following: the harvester system is adjusted by the hydraulic cylinders and placed with the bottom knife under water then, both knives are actuated. Because the reed grows 3000-4500 mm tall a second cut is needed at 1500 mm up to the first one. While the harvester advances, it cuts reed stalks within its operational range into two parts and directs them into the equipment's container. The harvester is driven by the two paddle wheels located at the back of the boat. When the storage hold becomes full, the reed harvester returns to shore to unload. The harvesting efficiency is given by finding the optimal settings

for forward speed, cutting speed and chain conveying speed, but at the same time consuming the least amount of energy.



(a) Manufactured equipment



(b) Key components design. 1. Assembled ponton, 2. Welded frame, 3. Double-blade cutterbar, 4. Paddle-wheel, 5. Conveyor, 6. Biomass collection bin, 7. Steering system with rudder, 8. User seat, 9. Electric batteries, 10. Plate indexing, 11. Electrical elements, 12. Hydraulic actuator, 13. Hydraulic knife drive motor, 14. Conveyor chain drive hydraulic motor, 15. Paddle drive hydraulic motor, 16. Electric motor, 17. Double pump, 18. Proportional distributor, 19. Sectional distributor, 20. Electronic control, 21. Remote control, 26. Converter

Fig. 3. Reed harvester experimental model (ERBA)

The float assembly consists of two floats 4.5 m long, with a diameter of 0.8 m at the bottom and a straight area of 0.7 m. Each float consists of 3 sections 1.5 m long, welded between them, hermetically sealed, being designed to float and slide on water. The front part has an aerodynamic shape, so as to reduce the frontal resistance exerted by the water mass, during the movement of the equipment. The two floats are attached to each other with 0.8 m long crossbars made of rectangular pipe. The floats were sized to ensure the buoyancy of a total mass of 2,5 tons with a maximum draft of 75% of the height of the floats.

The biomass collection bin is of metal construction, fixed, welded to the frame, which has a useful volume of 2,5 m³. The harvesting system comprises the frame, biomass conveyor and two double-blade cutter bars, positioned in a vertical plane at 1.5 m, one to the other. The conveyor is made up of flat aluminum slats and from place to place, with a serrated L profile to prevent the material from sliding into the water. The assembly features double-knife cutters with guide plates and triangular lamellar knives, which have reciprocating rectilinear movement, being individually actuated by a hydraulic motor. Right and left paddle wheels are the assemblies that ensure the propulsion of the boat, the active part is made up of 8 radially arranged curved paddles, operated by an OMR 100 hydraulic motor. The role of the paddles is both for movement and for turning left/right, the command being given with the help of a proportional distributor, which ensures the independence of the actuation as well as the change of speed, by changing the flow of oil transmitted to the electric motor, thus changing the speed of each vane, depending on the need. The over- all dimensions size of the harvester are (length×width×height)/ mm×mm×mm are 7800x2500x1800 and a total mass of 1880 kg.

5. Design of the electric actuation

Starting with the presented requirements, the electrical actuation main constraints are:

- the source of energy must be the electricity provided by a non-pollution means, like electric battery storage;
- the boat has to be conducted remotely, making possible the integration into an intelligent harvesting system;
- the power applied to the propulsion and to the auxiliaries has to be provided at low speed and high torque, with the best solution the use of hydraulic motors and actuators;
- the autonomy of this boat has to be greater than 2 hours of working time, for efficiency reasons.

The labor work law mandates that the voltage on electric boats should not exceed 65 Vdc due to restrictions in place. The proposed value of 33 kWh is resulting from combining the 60 Vdc with the requested autonomy and with the estimated instantaneous power needed for the knives cutting the reed, bringing the reed onboard using the conveyor and pushing with the paddles during the movement and harvesting.

The selected storage is comprising three Li-ION battery packs having a rated voltage of 58.4 Vdc and storage capacity of 11 kWh each, with three packs connected in parallel mode for redundancy and autonomy. The safety of the Li-ION packs is performed by individual BMS (Battery Management System) circuits, which can supervise each of the modules for ensuring protection against overvoltage, undervoltage, overcurrent, overtemperature, and correction of the current limit with the temperature of the modules. Additional tasks of the BMSs are the estimation of the State-of-Charge SOC and the control of the external charger in the vicinity of 95% SOC, and, also, in the case of abnormal battery temperature. For the conversion of the electric energy stored in the batteries into hydraulic power, an electric motor controlled by an electric drive is used. The most recommended solution is the use of an Internal Permanent Magnet Synchronous Motor IPMSM driven by a dedicated three-phase converter operating the motor in a speed closed-loop, based on a motor's internal speed encoder. The auxiliaries are using hydraulic power provided by the pump's main section driven by the electric motor, while the traction paddles are supplied from the secondary section of the hydraulic pump. The control of hydraulic oil flow through the various motors is controlled using electro-hydraulic distributors, both proportional and sectional ones. The oil is circulated through a cooler and a reservoir of 90L. The commands for the boat are provided using a dedicated remote controller, which can control the two paddles independently, in both directions, with linear torque control. The same remote controller is controlling, using switches, the auxiliary systems as the cutters, the loading belt, and the positioning actuators for the harvesting device. Fig. 4 displays the primary electrical diagram that includes the following elements M01 - electric motor, A01 - Converter, A02 - battery packs, A03 - external battery charger, A04 - connection box, and, also, the DC-DC converter A05 for supplying the controls with 12 Vdc, the sensors A06 involved in the AI complex functions interconnected with the electric equipment, and the vehicle controller unit A07.

Due to the intricate nature of the control system, the solution included a dedicated multi-processor architecture, based on radio communication between the remote controller and the boat, and using serial CAN communication with the batteries' BMSs, serial CAN communication with the motor's converter, and several pulse commands for hydraulic valves.

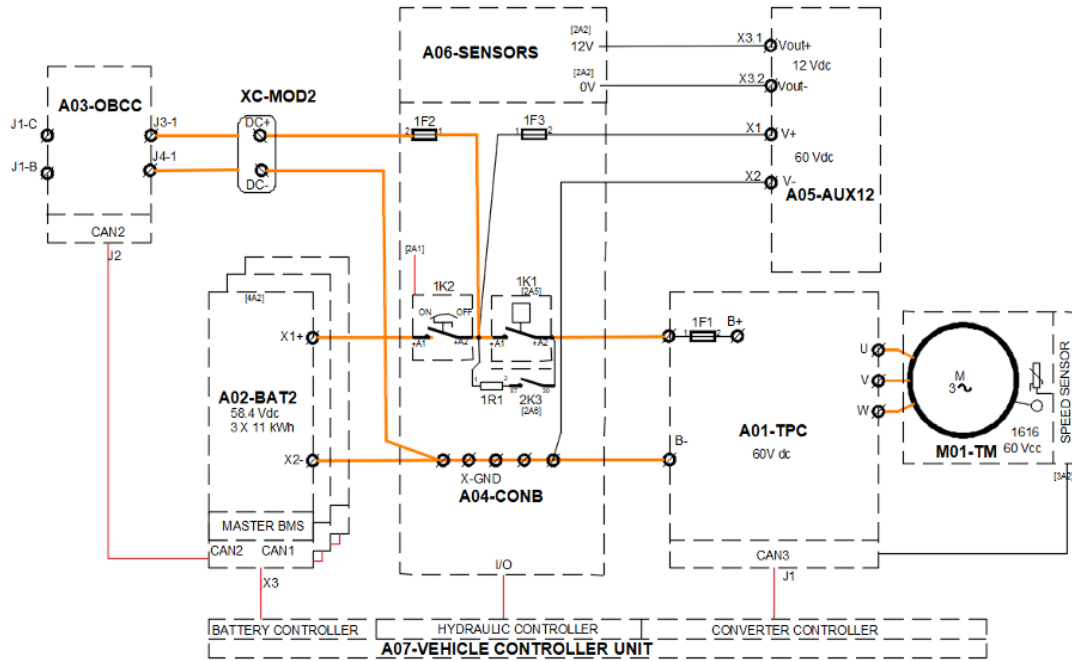


Fig. 4. Main electrical diagram – power elements.

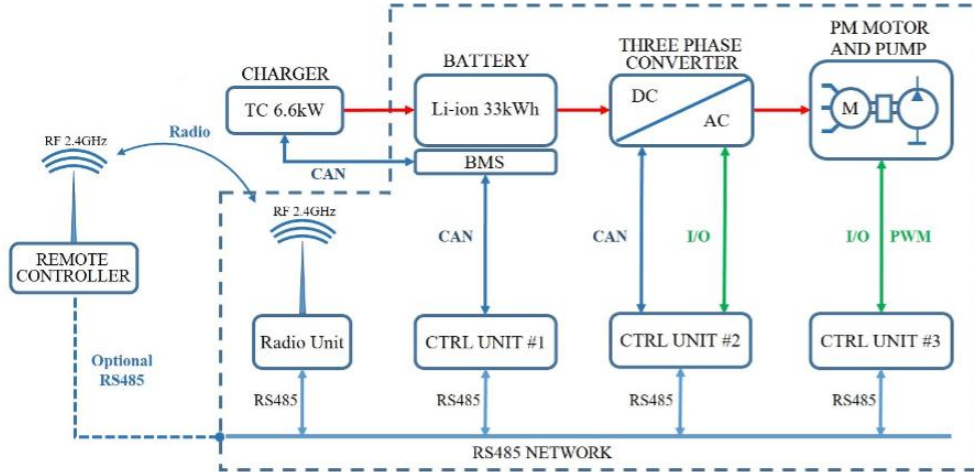


Fig. 5. Functional diagram of the control system.

The control units and their communications are presented in Fig. 5. The control system was developed using a step-by-step procedure, and each control procedure can be tested and debugged individually and independently from the operation of the other controlled arms. The software is described in detail in previous research [16].

6. Custom-built IoT monitoring station

In the design phase of the monitoring station, the primary aim was to adhere to the methodology outlined in Section 3 while also leveraging open-source IoT platforms and artificial intelligence (AI) tools. Far from the electric grid, sizing the power supply to a monitoring solution is crucial. In the power supply solution, an MPPT (Maximum Power Point Tracking) was used. The MPPT can be configured to output 12, 24 or 48V for the input of a maximum of 35A and 150V provided by a photovoltaic panel. As shown in Fig. 6 the MPPT system charges a battery that can provide power to the IoT monitoring solution for a duration of up to 48 hours on a single charge. The air quality sensor, depicted in Fig. 7, employs a data transfer mechanism that relies on RESTful API.

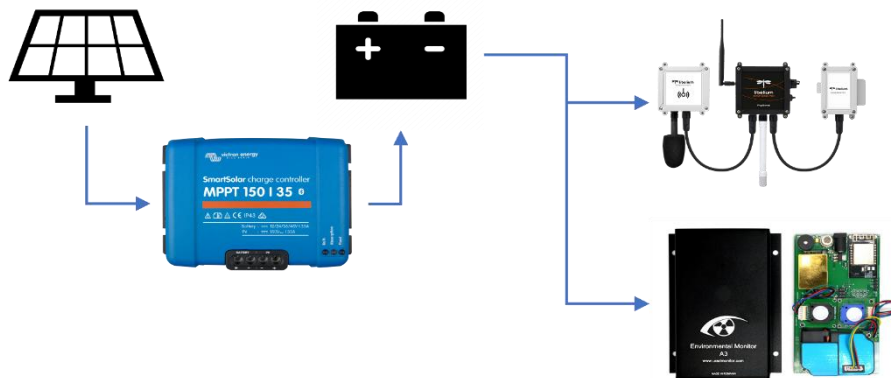


Fig. 6. Power supply for IoT remote monitoring.

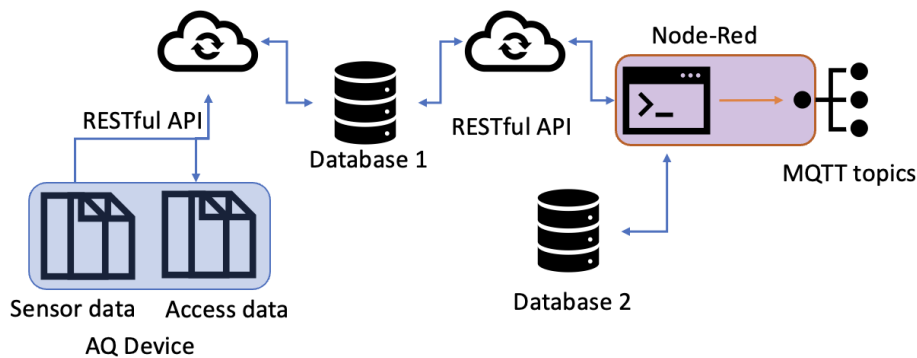


Fig. 7. Air quality sensor datapath

RESTful API facilitates the exchange of information through HTTP requests, encompassing data types such as GET, PUT, POST or DELETE for both input and output operations. For this case study as an integration tool, the Node-Red flow development tool was used. The software can unpack the received HTTP messages which are encapsulated in JSON format. As depicted in Fig. 8, the trigger

for data retrieval is an MQTT (Message Queuing Telemetry Transport) message or a trigger. Following the data path, a request message is generated and sent afterwards to the vendor’s server using HTTP communication. The HTTP response is processed by a JSON parser, and the encapsulated data is stored in an MSSQL (Microsoft Structured Query Language) database on a local cloud after being processed by the function block IAQ processing. Furthermore, the application includes an MQTT publisher that enables the transmission of processed data to third-party applications or stakeholders.

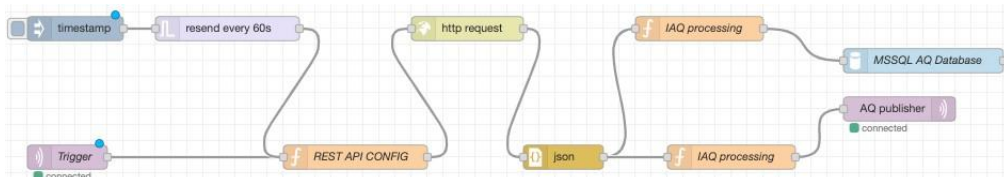


Fig. 8. Data workflow for air quality monitoring

For water quality monitoring, the communication relies on the MQTT protocol, an IoT messaging standard operating over TCP/IP. In terms of data representation, the solution makes use of the JSON format. As illustrated in Fig. 9, the data path is similar to air quality monitoring. In the event of an internet connection failure, the solution is designed to store the information temporarily on a local storage unit. Another essential aspect highlighted in section 3 is the selection of quantifiable elements in the monitoring system and the accuracy of the sensors. In the following table, Table 1, are presented technical characteristics of the sensors included in the solution. The solution is subscribed, through MQTT, to 5 parameters, namely temperature, dissolved oxygen, pH, conductivity, and oxygen-reduction potential.

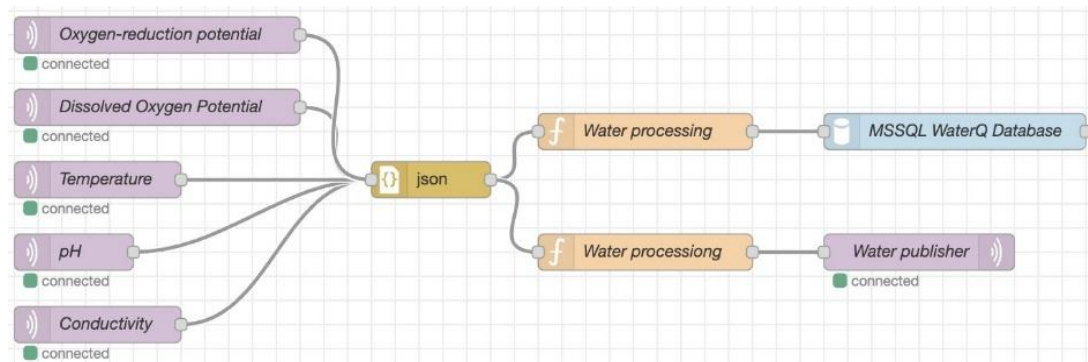


Fig. 9. Workflow capture for water quality monitoring.

Furthermore, the water quality monitoring solution includes an MQTT publisher that enables the transmission of processed data to third-party applications or stakeholders.

Table 1.

Air and Water quality technical specification of the sensors			
Parameter	Reference interval	Resolution	Accuracy
Temperature	[-40 , +85] °C	0.5°C	±1°C
Humidity	[0 , 100] %RH	%RH	±1%
PM1	[0 , 1000] μG/m ³	1μg/m ³	R=0.99
Pm2.5	[0 , 1000] μG/m ³	1μg/m ³	R=0.99
Pm10	[0 , 1000] μG/m ³	1μg/m ³	R=0.99
CO2	[400 , 5000] ppm	1ppm	±5%
Formaldehyde	[0 , 5] ppm	10ppb	±5%
Ozone	[0 , 10] ppm	10ppb	±5%
VOCs	[10 , 1000] ppm	-	±5%
Noise level	[30 , 130] dB	1dB	±1%
Dissolved Oxygen	[0 , 20] mg/L	-	±2%
pH	[0 , 14] mg/L	-	0.01%
Temperature	[0 , 100] °C	0.01	±1%
Oxidation-reduction potential	[0 , ±1999] mV	-	-

As with the case of air quality monitoring, the water quality monitoring solution stores the data on a local cloud platform. In addition to sensor data processing and storage, the cloud platform for monitoring employed Grafana, an open-source, multi-platform tool, to facilitate data visualization, transfer, and analytics. In Fig. 10, are presented 8 air quality parameters, namely PM 1, PM10, Temperature, CO₂, Ozone, Humidity, VOC and Noise. The parameters were collected using a time rate of 5 min. For each time series, a prediction AI algorithm and training accuracy were analyzed. The results were stored in a local cloud.



Fig. 10. Air quality parameters.

7. Long Short Term Memory AI algorithm for time-series forecastin

Trend prediction is a research field which made promising advancements, especially due to machine learning and artificial intelligence (AI). Deep learning, a subset of machine learning, is based on artificial neural networks (ANN). It has gained significant attention in recent years due to its success in a wide range of applications, including time-series forecasting, data fault detection, computer vision, image processing, and speech recognition. At its core, as depicted in Fig. 11, an artificial neural network (ANN) consists of layers of interconnected nodes that perform iterative calculations and transfer the data to upper layers based on activation function.

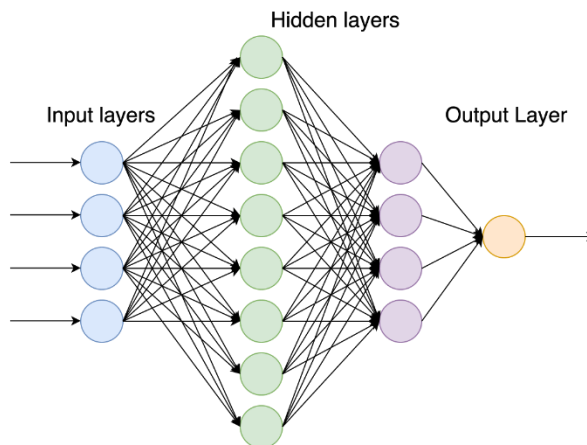


Fig. 11. Artificial Neural Network architecture

LSTM addresses two fundamental limitations of Recurrent Neural Networks (RNNs): the vanishing gradient and the exploding gradient problems. In this study, the Long Short-Term Memory (LSTM) algorithm, a widely applied technique in deep learning, was employed. Since its first publication [17], the algorithm has been widely used, among others, in applications which require processing sequential data, such as forecasting or time-dependent data.

In 1997, Hochreiter and Schmidhuber [17] introduced the Long Short-Term Memory (LSTM), a modified form of Recurrent Neural Networks (RNNs), designed to address the vanishing gradient problem. The hidden layer in the RNNs is replaced by an LSTM cell. The LSTM cell consists of three gates: forget gate, the input gate and the output gate. These gates control the amount of long-term and short-term memory generated and retained by the cell. Hidden layers were introduced in a two-layer network to overcome the limitation of the XOR operation, which cannot be performed before. The hidden layer is an intermediate layer that contains the activation function and plays a significant role in the LSTM network. One advantage of LSTM over traditional RNNs is that the constant error backpropagation through its memory cells enables it to capture dependencies across very long-time intervals. In addition, LSTM networks can handle noise, distributed representations, and continuous values in problems involving extended time lags.

Compared to the RNN, LSTM solves the problems of gradient exploding and vanishing gradient by adding memory cells. The standard LSTM architecture has input, recurrent LSTM layers also known as hidden layers and an output layer. The difference between LSTM and RNN is that LSTM replaces the hidden layer neurons of the RNN with a special structure that is presented in Fig. 12. As presented in Fig. 12, the LSTM structure includes several gates which track the sequence information and it's composed of an input gate, forget gate, and output gate. The function of the input gate is to determine which information should be preserved for the next state, while the forget gate identifies the information that should be discarded from the current state data [18].

The basic LSTM cell is composed of x as the input to the cell, h as the short-term memory and c as the long-term memory. The subscript for x , h and c refers to the timestep. For an LSTM iteration example, if the calculation returns 0, that means full retention of that data and if the calculation returns 1, this means full discard of that data. The output gate determines the information in the state be routed to the output. In this case study, we introduced the application of the LSTM model in time-series forecasting based on water and air quality parameters. By performing the experiment based on a real dataset, the result proves that choosing the appropriate number of hidden units is important for the training accuracy and training time of neural networks.

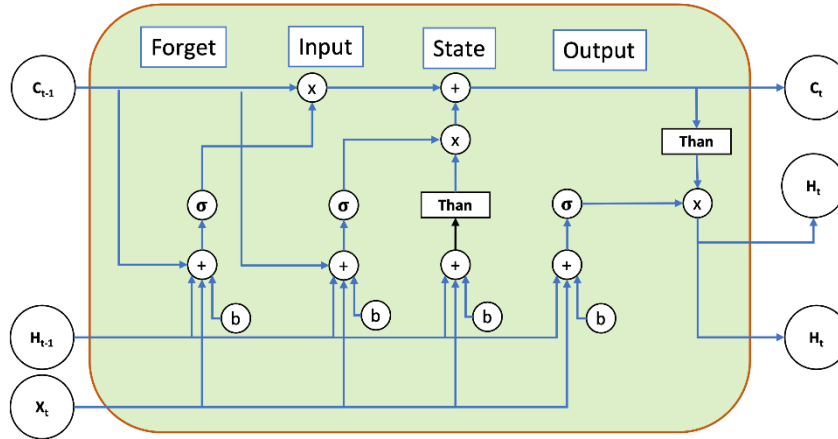


Fig. 12. Artificial Neural Network architecture.

The issue training of the LSTM is based on how many hidden layers should be used to solve complex problems. The number of neurons in the hidden layer will significantly affect the final performance of the overall network architecture and the lack of relevance in training a model with high accuracy.

In the forecasting simulations, the goal was to find a moving window training set with optimal training set data and optimal LSTM nodes and an optimal number of epochs, given the computational power available. The testing dataset included, initially, 85000 values which represented the evolution of CO2 emissions, out of which, the training set included nearly 70000 values. Fig. 13 presents both actual and predicted values of the training set. As it can be observed, the predicted values are closely approximating the actual values.

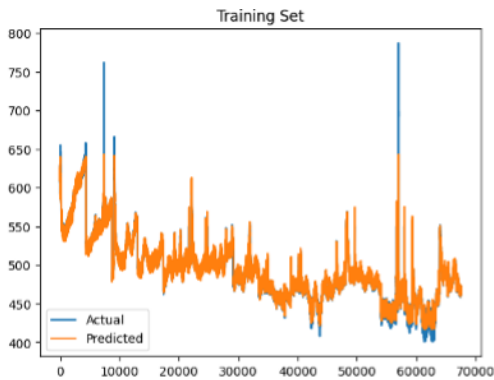


Fig. 13. Training dataset for LSTM neural network.

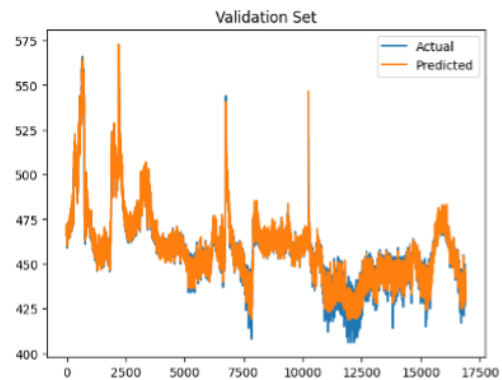


Fig. 14. Validation dataset for LSTM neural network.

In Fig. 14 it can be analyzed how the validation set performs in terms of forecasting the actual values. Regarding the qualitative assessment of LSTM performance, two measures were employed: the root mean square values and the validation loss curve.

Validation loss curves show how the neural network is performing during data training in terms of learning and how well it is adapted to unseen data.

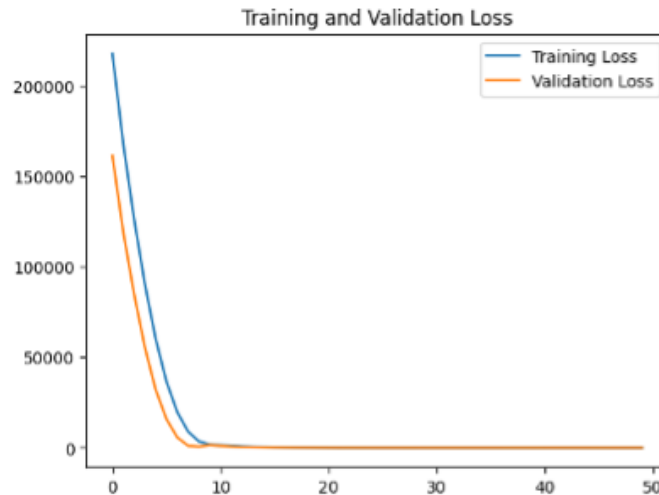


Fig. 15: Validation loss curve.

As shown in Fig. 15, during the first 10 epochs the training loss is decreasing due to the adjustment of the LSTM node. The training and validation loss is eventually converging to 0, showing that the model fits the data and will perform well during the processing of new data.

8. Conclusions

The article proposes a practical solution for preserving the fragile and diverse biosphere of the Danube Delta Reserve, aligned with the EU Biodiversity Strategy for 2030 and its Action Plan. It introduces a specially designed electric reed harvester equipped with a custom monitoring station that integrates IoT architecture and AI-based predictive capabilities for air and water quality assessment. The experimental self-propelled harvester has an autonomy of over 1.5 hours and can collect aquatic biomass for potential biofuel applications. The monitoring system integrates multiple sensors through open-source solutions, ensuring data acquisition, transmission, visualization, storage, and analysis via cloud platforms using RESTful API and MQTT protocols. Predictive modeling is implemented using an LSTM neural network applied to environmental parameters. Future work includes deploying stationary monitoring stations to extend spatial

coverage and enable large-scale data analysis. In addition, future research will focus on scalability and transferability, enabling the deployment of the proposed solution in other protected areas across Europe. The proposed system supports the need for high-quality, homogeneous environmental data and contributes to ecosystem restoration efforts, awareness raising, and mitigation of natural disaster impacts.

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REFERENCES

- [1] U. Nations, Transforming our world: The 2030 agenda for sustainable development. goal 17: Partnerships for the goals, <https://sdgs.un.org/2030agenda> (2015).
- [2] E. Commission, Communication from the commission to the european parliament, the european council, the council, the european economic and social committee and the committee of the regions: The european green deal.,<https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020SC0176> (2020).
- [3] A. P. D. Dinu, Danube delta, the largest wetland in europe, <https://romanasalbatica.ro/ro/rezervatie-biosfera/delta-dunarii> (2021).
- [4] E. E. Policy, Eu environmental policy in environment action programmes, <https://wecoop.eu/regional-knowledge-centre/eu-policies-regulations/>.
- [5] E. Commission, Conservation of natural habitats and of wild fauna and flora, <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:31992L0043> (1992).
- [6] I. C. for the Protection of the Danube River, <https://www.icpdr.org/main/icpdr/about-us>.
- [7] E. Commission, Biodiversity strategy for 2030, https://environment.ec.europa.eu/strategy/biodiversity-strategy-2030_en (2022).
- [8] D. N. Paithankar, A. R. Pabale, R. V. Kolhe, P. William, P. M. Yawalkar, Framework for implementing air quality monitoring system using lpwa-based iot technique, *Measurement: Sensors* 26 100709. doi:<https://doi.org/10.1016/j.measen.2023.100709>.
- [9] S. V., S. A., Lstm-markov based efficient anomaly detection algorithm for iot environment, *Applied Soft Computing* 136 (<https://doi.org/10.1016/j.asoc.2023.110054>, 2023) 110054.
- [10] T. Popovic, N. Latinovic, A. Pesic, Z. Zecevic, B. Krstajic, S. Djukanovic, Architecting an iot-enabled platform for precision agriculture and ecological monitoring: A case study, *Computers and Electronics in Agriculture* 140 (<https://doi.org/10.1016/j.compag.2017.06.008>, 2017) 255–265.
- [11] N. Chamara, M. D. Islam, G. F. Bai, Y. Shi, Y. Ge, Ag-iot for crop and environment monitoring: Past, present, and future, *Agricultural Systems* 203 (<https://doi.org/10.1016/j.agry.2022.103497>, 2022).
- [12] T. Domínguez-Bolaño, O. Campos, V. Barral, C. J. Escudero, J. A. García-Naya, An overview of iot architectures, technologies, and existing open-source projects, *Internet of Things* 20 (<https://doi.org/10.1016/j.iot.2022.100626>, 2022).
- [13] F. N. Güttler, S. Niculescu, F. Gohin, Turbidity retrieval and monitoring of danube delta waters using multi-sensor optical remote sensing data: An integrated view from the delta plain lakes to the western–northwestern black sea coastal zone, *Remote*

- Sensing of Environment 132 (<https://doi.org/10.1016/j.rse.2013.01.009>, 2013) 86–101.
- [14] N. Damian, B. Mitrică, I. Mocanu, I. Grigorescu, M. Dumitras, cu, An index-based approach to assess the vulnerability of socio-ecological systems to aridity and drought in the Danube Delta, Romania, *Environmental Development* 45 (<https://doi.org/10.1016/j.envdev.2022.100799>, 2023).
- [15] V. Tanasiev, G. C. Patru, D. Rosner, G. Sava, H. Necula, A. Badea, Enhancing environmental and energy monitoring of residential buildings through IoT, *Automation in Construction* (<https://doi.org/10.1016/j.autcon.2021.103662>, 2021).
- [16] E. Tudor, M.-G. Matache, I. Vasile, I.-C. Sburlan, V. Ștefan, Automation and remote control of an aquatic harvester electric vehicle, *Sustainability* 14 (10). doi:10.3390/su14106360.
- [17] S. Hochreiter, J. Schmidhuber, Long Short-Term Memory, *Neural Computation* doi:10.1162/neco.1997.9.8.1735.
- [18] K. Moharm, M. Eltahan, E. Elsaadany, Wind speed forecast using lstm and bi-lstm algorithms over gabal el-zayt wind farm, in: 2020 International Conference on Smart Grids and Energy Systems (SGES), 2020, pp. 922–927