Sustainable Solutions for Sea Monitoring with Robotic Sailboats: N-Boat and F-Boat Twins

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ABSTRACT

Strategic management and production of internal energy in autonomous robots has becoming a research topic with growing importance, especially for platforms developed for long endurance missions, with long range and duration. It is important for autonomous vehicles to have some energy self-generation capability in order to improve energy autonomy, especially in situations where refueling is not viable, as for example an autonomous sailboat in ocean traversing. The development of energy estimation and management solutions are an important research topic in order to better optimize the use of available energy supply and generation potential. In this work we revisit the challenges behind the project design and construction of two fully autonomous sailboats and propose a methodology based on Restricted Boltzmann machine (RBM) aimed to find the best way for energy distribution and consumption, for managing the energy generated by solar panels. We describe a specific case of our sailboat that are equipped with an electrical engine that may eventually help with the sailboat propulsion. Our current results show that it is possible to augment the system confidence level for the potential energy that can be harvested from the environment and the remaining energy stored, optimizing the energy usage of autonomous vehicles and improving its energy robustness.

Keywords: Autonomous Sailboat; Energy Self-generation; Energy Management; Renewable Energy; Boltzman Machine

1 INTRODUCTION

Autonomous vehicles are machines that have embedded systems with some specific purpose that depends on the application. In general, they have computational and physical resources restrictions (Almeida, 2016), being energy performance one of the main issues to be accounted when developing such machines (Aldegheri et al., 2018). Surface aquatic robotic (ASV or USV) and submersible (AUV) vehicles allow human beings to explore the ocean in innovative ways, with less cost, greater efficiency and reducing risks inherent to marine operations, quickly following its natural course towards its ultimate goal: full automation of working in the ocean. An emerging generation of devices and their systems is being designed and developed to operate independently, making decisions during operation, without direct control of a human operator.

Nonetheless, there are several cases where energy autonomy is still a big issue, contrasting with its reliability in the face of day-to-day missions (Alaieri and Vellino, 2016). Energy autonomy refers to the robotic agent's ability to maintain itself in a viable state for long periods of time, or as necessary. Its behavior must be always stable in such a way that it does not lack any vital resource. For example, in some situations it must not exceed some limit from which it cannot return to the beginning of a mission or to a safe point. Until recently, autonomy have been always approached from a computing perspective. For example, consider the case of a battery-operated robot that is released to perform its task without outside intervention. When the task is completed or when the battery charge decreases, the robot returns to a base for recharging and/or further instructions. Thus, certain aspects of robot behavior can be considered autonomous, for example, computational and control decisions. On the other hand, without a human in the *loop*, the robot would not be able to replenish its energy to perform the task.

In this paper we introduce a novel project inspired by its previous versions (Júnior et al., 2013; Negreiros, 2019), whose main objective is the development of an autonomous vessel for collecting and monitoring environmental data. This is an open project, with complete documentation can be found at the web repositories (LAICA, 2015; Negreiros, 2019). The main focus of the project is to develop a long endurance autonomous system, satisfying quality criteria for being qualified as sustainable and with environmentally friendly energy generation.

Figure 1. F-Boat hull with its solar panels.

The current project version named F-Boat is an evolution of our previous USV projects that our research group has developed, such as the N-Boat 1 (Júnior et al., 2013) and N-Boat 2 (Negreiros, 2019). Actually, F-Boat is a twin, new version of N-Boat 2 with updated architectural design and equipment. It is also an autonomous unmanned vessel (a sailboat USV) as seen in Figure 1. In this newer version, in addition to the sensors necessary for autonomous navigation, other more dedicated sensors are used, such as a stereo camera with a 20 meters range for forward visual sensing and a 360 camera for short range visual sensing.

Both sensors playing the role of perceiving the environment and finding short-range obstacles. All of these sensors generate a massive amount of data that are locally processed by an embedded processor, which is based on an nVidia Xavier single board computer. These data can also be sent to a ground station, which is an option for mission update or telemetry. In addition, part of this data is saved locally for future analysis and comparison with a simulator that has been implemented.

Hence, the general contribution of the project is a step forward for solving the several challenges faced when developing a sailboat robot, beginning with the boat's architectural design and construction itself, including solutions for autonomous sailing navigation, image processing, obstacle detection, control issues, and energy management.

Nonetheless, one contribution focus of this paper resides on describing reliably and ecologically correct solutions to both sailboats' energy problems. We propose a solution that involves the use of *offgrid* energy production based on solar panels in order to maintain the more complete as possible set of components operating, such as an emergency electric motor, actuators, processors, and cameras. Thus, it is necessary to make an intelligent use of the scarce energy resource, aiming at an autonomous, sustainable, and ecologically correct system. As a second contribution, we propose here a set of rules that are implemented for setting up what are the devices that can operate given certain weather conditions to the sailboat, including emergency cases. This managing is implemented by way of using a Boltzman Machine (Bu, Yude et al., 2015; Passos et al., 2020). Our current results demonstrate that its use is in the right direction, appearing to be a good idea towards a solution to this kind of problem.

Some theory on sailboat projects are introduced in the following Section, in which we will also describe the basics of the Boltzman machine that will be the intelligence approach behind the vehicle's energy resource. Then we provide the energy generation system followed by the use of Boltzman machine approach, with a experiment on energy management and our final discussions.

2 BACKGROUND ISSUES RELATED TO AUTONOMOUS SAILBOAT

A sailboat that intends to operate at the sea gives up important challenges that are brought by physical environmental phenomena such as waves, wind, water salinity, and temperature, between others. Most of these phenomena can be represented by dynamic variables, which is one natural alternative for building, analyzing and comparing techniques for autonomous sailing. In order to better understanding and for designing and implementing a fully autonomous sailboat, it is necessary to get together some multidisciplinary contents. In this Section we get into some of these, with important issues related to the energy management, architectural design of our sailboat, and details of Boltzman machine energy management solution.

2.1 Renewable Energy Sources in Sailboats

The usage of renewable sources, such as the sun, wind, tides, among others are important ways for enhancing the energy autonomy in future vehicles (Dupriez-Robin et al., 2009). In this direction, the use of wind propulsion is an important solution for surface water autonomous vehicles (USV or ASV). However, to ensure that a sailboat is an electrically self-sufficient platform, since all on-board electronics require one or more energy sources, considerations must be taken regarding the total energy required and how much operating time will be spent on the missions. Rechargeable batteries are typically used as primary sources for energy storage. It is essential to consider on-site energy production using some self-sustaining model. On vessels, there are several ways to obtain energy. One of the most used are solar panels, which is an excellent alternative energy source for embedded systems in general (Raghunathan et al., 2005).

Solar panels are devices that convert energy from solar radiation into electrical energy. However, depending on factors involving the panels nature, such as direct radiation, hours of sunlight and temperature, substantial variations in the amount of energy produced by these mechanisms can occur. It is necessary to use a charge controller, which stabilizes varying energy ranges. As occurs in any transformation process in nature, a part of the energy is lost. Thus, the price of this transformation is a decrease in the energy efficiency rate of the system as a whole.

It is important to mention that choosing a sail-powered vessel is a strategic and main point of long range monitoring projects. Since we choose well-designed energy sources and also use well-defined consumption strategies (Letafat et al., 2020; Vu et al., 2017; Khan et al., 2017; Kanellos, 2014), sailboats are able to achieve full autonomy, acting independently of human beings, as long as they are programmed for the task. A fully autonomous robotic sailboat does not need to stop for recharging or refueling (Hole et al., 2016). In cases of semi-autonomy, recharging strategies during the mission must be considered and planned (Waseem et al., 2019a). The architectural design adopted in our sailboat is described next.

2.2 N-Boat and F-Boat Behavioral Architecture

As aforementioned in the Introduction, F-Boat is an upgrade of the previous autonomous sailing boat called N-Boat. Both of them are implemented based on a behavioral architecture, namely, subsumption (Brooks, 1986), which constantly process and executes routines of the different layers. With this approach, the basic actuation and sensing commands never cease to be executed. This architecture requires that the definition of all vehicle control behaviors that must be completely defined, observing the dependencies that each layer imposes to the others. Figure 2 illustrates the implementation of this approach.

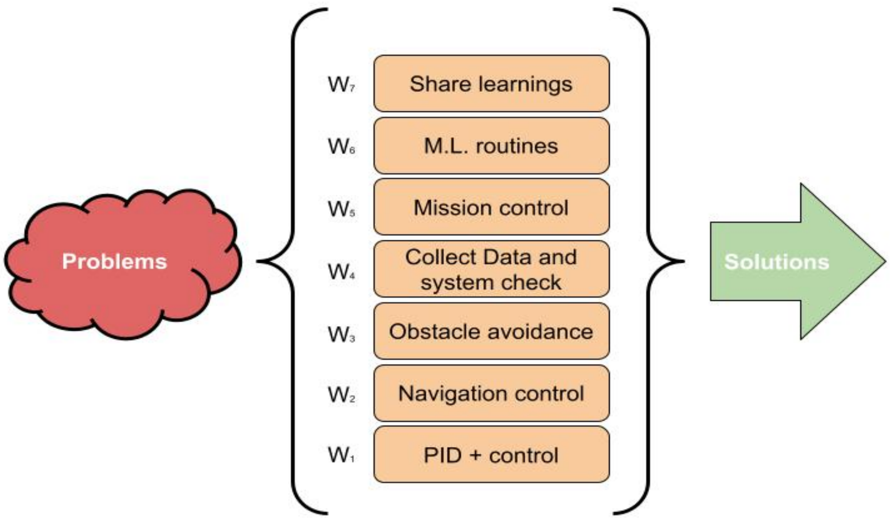

Figure 2. Basic subsumption architecture.

In the next control level subsumption architecture, weights behaviors will be constantly adjusted to adapt in real time to the environment. An abstracted representation of the objective of this proposal can be seen in Figure 2. These adjustments will be processed by a machine learning model. However, as the marine environment (wind, tides, weather, swells, etc.) is very dynamic, there is a great need for the weights of these behaviors to quickly adapt. In cases where regular algorithms are not able to perform this task in the required time, the option of using TEDA-Cloud is listed as an alternative. For instance, if data processing

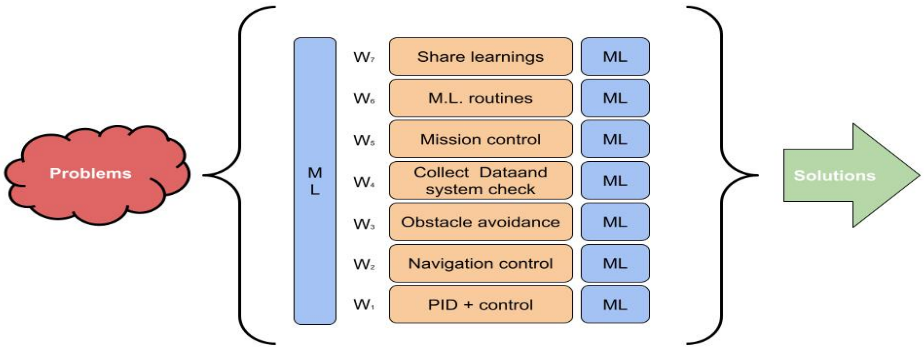

Figure 3. Subsumption combined with ML architecture.

can be made available online, it is possible to establish a window in which the signals can be processed with a greater degree of dynamicity (Bezerra et al., 2016).

We notice that, with current embedded computing resources, there is the possibility that behaviors can be computed at the same time. Since many control cards already have more than one physical core in the processor and chips or GPU cards. Therefore, it is quite plausible that these architecture can delegate more than one processing at the same time, which means that it may be possible for the boat to compute the processing of an obstacle avoidance while analyzing the processing of a payload, or the running energy management system based on the Boltzman machine.

Hence, we propose a sailboat control architecture that is focused for an energy-saving strategy. Since the behaviors also have energy consumption grades, routines that consume energy may be suppressed. Its important to mention that ML (Machine Learning) can learn to predict these cases, minimizing the situations where these events may happen.

2.3 Restricted Boltzmann Machine

The data classification problem is intrinsically related to the recognition of patterns and regularities in a given database. In the context of learning systems, classifying data is considered a supervised problem. However, unsupervised approaches, such as the restricted Boltzmann machine (Hinton, 2002; Smolensky, 1986) and autoencoders (Bourlard and Kamp, 1988) have been applied as feature extraction tools to feed supervised algorithms such as artificial neural networks (Haykin, 1999). Thus, semi-supervised techniques emerge, which have gained prominence in recent years.

The restricted Boltzmann machine (RBM) is a stochastic network widely used to compose deep belief networks (DBN) (Hinton and Salakhutdinov, 2006). RBM is able to extract characteristics from a dataset through unsupervised training. Due to this, approaches that use RBMs to compose a DBN were developed as the first stage of a classifier based on artificial neural networks (Salama et al., 2010; Tamilselvan and Wang, 2013).

The restricted Boltzmann machine (Smolensky, 1986; Hinton, 2002) is basically a stochastic network consisting of two layers: visible and hidden. The visible units layer represents the observed data and is connected to the hidden layer, which in turn, must learn to extract characteristics from this data (Memisevic and Hinton, 2010). Originally, RBM was developed for binary data, both in the visible layer and the hidden layer. This approach is known as Bernoulli-Bernoulli RBM (BBRBM). Due to the fact that there are problems where it is necessary to process other types of data, Hilton and Salakhutdinov (Hinton and

Salakhutdinov, 2006) proposed the Gaussian-Bernoulli RBM (GBRBM), which uses a normal distribution to model the visible layer neurons. In this section, the basic concepts related to the GBRBM approach will be described.

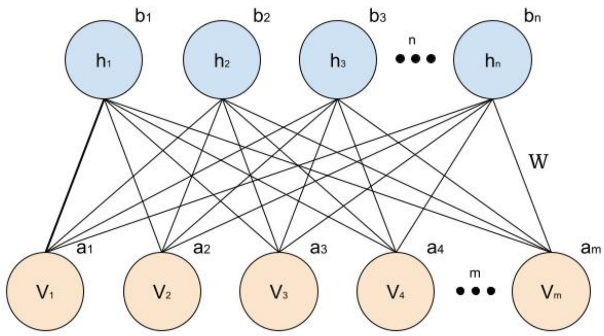

Figure 4. A simple Restricted Boltzmann Machine architecture.

In RBM, the connections between neurons are bidirectional and symmetrical. This means that there is information traffic in both directions of the network. Furthermore, to simplify the inference process, neurons from the same layer are not connected to each other. Therefore, there is only a connection between neurons from different layers, so that the machine is restricted. Figure 4 shows an RBM with M neurons in the visible layer $(v_1, ..., v_m)$, n neurons in the hidden layer $(h_1, ..., h_n)$, where $(a_1, ..., a_m)$ and $(b_1, ..., b_n)$ are the bias vectors and W corresponds to the connection weight matrix. From here to the end of section 2, the set (W, a, b) will be called θ.

$$p(\mathbf{v}, \mathbf{h}; \theta) = \frac{e^{-E(\mathbf{v},\mathbf{h};\theta)}}{\sum_{\mathbf{v},\mathbf{h}} e^{-E(\mathbf{v},\mathbf{h};\theta)}} \tag{1}$$

The RBM is an energy-based model, with the joint probability distribution of the configuration (v,h) being described by:

$$E(\mathbf{v}, \mathbf{h}; \theta) = \sum_{i=1}^{m} \frac{(v_i - a_i)^2}{2\sigma_i^2} - \sum_{j=1}^{n} b_j h_j \sum_{i,j=1}^{m,n} \frac{(v_i)}{\sigma^2} h_j w_i, j \tag{2}$$

As the RBM is restricted, that is, it does not have neuron connections between the same layer, the probability distributions of h given v and v given h are described by Equation 3 and Equation 4, respectively.

$$p(\mathbf{h}|\mathbf{v}; \theta) = \prod_j p(h_j|\mathbf{v}) \tag{3}$$

$$p(\mathbf{v}|\mathbf{h}; \theta) = \prod_i p(v_i|\mathbf{h}) \tag{4}$$

The Restricted Bolztmann Machine that we use here is implemented using Python, with the Numpy, Keras and Sklearn library help. After training, this network is able to predict the future vessel's dynamic consumption 24 hours ahead. We use here data collected from previous missions by the F-Boat's predecessor vessel (N-Boat), as the sensors provided data on wind position and intensity, tides, vessel instantaneous energy consumption, sail position and rudder position. This information is used as input to the neural network, which begin its learning process by processing these data with a bias lower than 0.01%.

Table 1. Strictly related works.

Title	Vehicles	Focus	Citation
Design of a Battery Carrying Barge for Enhancing Autonomous Sailboat's Endurance Capacity	USV Sailboat	Energy endurance	Liang et al. (2021)
Design and Energy Consumption Optimization of an Automatic Hybrid Sailboat	USV Sailboat	Energy optimization	Ou et al. (2021)
Unmanned Surface Vehicle Simulator with Realistic Environmental Disturbances	USV Sailboat	Sailboat simulation	Paravisi et al. (2019)
Offshore Sensing SailBuoy Unmanned Surface Vessel	USV Sailboat	Long endurance surface vehicle	Sailbuoy (2018)
Autonomous Sailboat Navigation	USV Sailboat	Many	Stelzer and Jafarmadar (2007)
Routing and course control of an autonomous sailboat	USV Sailboat	Trace efficient routes using PRM-Dijkstra	Saoud et al. (2015)
High-Level Path Planning for an Autonomous Sailboat Robot Using Q-Learning	USV Sailboat	Sailboat navigation	da Silva Junior et al. (2020)
A Behavior-Based Architecture for Realistic Autonomous Ship Control	General boats USV	Describe methodology	Olenderski et al. (2006)
An experimental comparison of hierarchical and subsumption software architec- tures for control of an auto= nomous underwater vehicle	AUV Submarine	Compare architectures	Byrnes et al. (1992)
Reinforcement Learning in a Behaviour-Based Control Architecture for Marine Archaeology	AUV submarine	Controle de submarinos	Frost et al. (2015)
Control architectures for autonomous underwater vehicles	AUV Submarine	Survey and control of AUVs	Valavanis et al. (1997)
A Hybrid Control Architecture for Autonomous Robotic Fish	AUV Robot Fish	Collaborative control between fish robots	Liu et al. (2006)
Functional system architectures towards fully automated driving	AV Cars	Survey and car control	Taş et al. (2016)
Development of Autonomous Car—Part II: A Case Study on the Implementation of an Autonomous Driving System Based on Distributed Architecture	AV Cars	Car control	Jo et al. (2015)
V-stability Based Control for Energy-saving Towards Long Range Sailing	USV Sailboat	Energy saving	Sun et al. (2021)

3 SIMILAR PROJECTS (STATE OF THE ART)

Literature related to nautical autonomous vehicles is scarce, when compared to other types of autonomous vehicles. At this point, we present the most relevant works related to the research topics of this one, mainly for comparison. As organizational criteria, all comparisons are described in Table 1 and their comments can be found in the following text. Notice that other types of vehicles appear in the table besides unmanned surface vehicles (USV), including autonomous underwater vehicles (AUV), and autonomous vehicles (AV).

The Sailbuoy team (Sailbuoy, 2018) is known to be the first sailboat that completed the Microtransat challenge (Microtransat, 2021) in June 2018. But, in that occasion the sailboat was not fully autonomous, being remotely controlled at some parts of the cross. Besides, it has proven to be efficient, staying for months at sea transmitting and receiving data. This sailboat can be used in applications as measuring ocean parameters (Hole et al., 2016), tracking oil spills, or as a communication relaying station.

Competitions are an important source of references in sailing robotics, as occurs in other robotic fields such as the world robot soccer competition (Robocup). Examples of international competitions related to robotic sailboats are the *World Robotic Sailing Championship (WRSC)*, derived from the *The Microtransat Challenge*, which is a competition between autonomous sailboats aiming to cross the Atlantic Ocean. Other sailboats from Table 1 (Stelzer and Jafarmadar, 2007) and also from the literature (Stelzer, 2013; Dahl et al., 2015; Alves and Cruz, 2008) were developed thinking to compete in this challenge.

Further, we select from Table 1 three examples of works dealing with energy management in autonomous sailboats. The first one (Sun et al., 2021) deals with energy control methods for saving energy by improving the navigation system. The second (Liang et al., 2021) tries to increase energy autonomy by changing the hull structure to carry more battery packs. And the topic of the last one (Ou et al., 2021) is about optimizing energy by improving the use of the motor in hybrid sailboats (sail and engine).

Finally, besides having the two twin sailboats constructed, we also consider using another simulation environment that we have built based on the N-Boat specifications (last item of Table 1) (dos Santos and Goncalves, 2019; Paravisi et al., 2019). By using simulators it is possible to customize the same variables for different vehicles, as often as necessary. Simulated environments are a viable startup test bed that provides an initial performance for sailboat systems, tested in multiple environments, due the aforementioned particularities and because of the number of scenarios that can be considered. For example, the Boltzman machine can be implemented and tested in this environment, before a practical implementation.

4 POWER GENERATION SYSTEM

Even an autonomous sailboat consumes electricity to move around. Despite converting wind into kinetic movement, electrical energy is needed for its intrinsic components, which are the emergency and maneuvering electric propulsion engine, the rudder and sail actuators, the on-board computer, sensors and the payload. Currently, the N-Boat and F-Boat power generation system are purely fed by solar panels and a bank of nautical batteries. Details of this generation, storage and other alternatives will be treated in the next sections. This current generation is what is needed for long-term missions (Boas et al., 2016), which do not use the electric propulsion engine. The main hypothesis of this work is to allow propulsion engine use, without compromising the boat's energy supply in these missions. Therefore, it is necessary to use a strategy that allows, at certain times, under certain circumstances, its use during short period of time.

4.1 Energy generation approaches

Self-sufficient autonomous vehicles can generate energy in a number of ways. In this work we classify the sources into renewable (ecological) and non-renewable. The renewable correspond to Hydraulic, wind, solar, geothermal, marine, biomass and biogas. The non-renewables are oil, natural gas, coal and nuclear. Although there are many possible sources to be shipped, few are feasible, as illustrated in Figure 5.

Renewable sources, in addition to being ecologically correct, allow for long-term missions. Several studies (Wang et al., 2008; Waseem et al., 2019b) demonstrate that this alternative ends up being one of the best choices but requires strategies that guarantee a positive energy balance at the end. Since propulsion

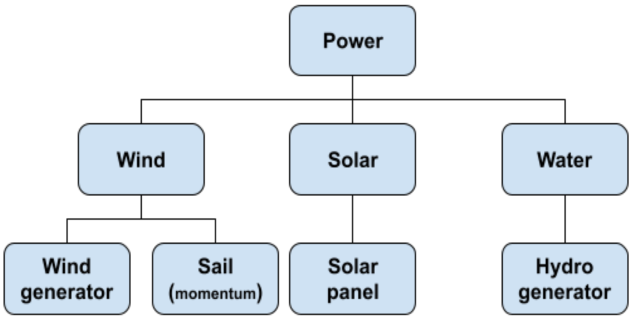

Figure 5. Energy generation approaches.

is the main energy consumption item of autonomous vehicles, there is a notable difference in energy autonomy between sailboats and other types of autonomous vehicles that are propelled by engines.

For a better hardware architecture understanding we present the solution based on the N-Boat and F-Boat models. Figure Figure 6 illustrates all components that generate or consumes some type of energy in this vessels. An important point is the electric motor, which, as will be shown later on, its continuous use can compromise the entire vehicle autonomy. Therefore, the solution needs a strategy that only allows its use in special moments, such as, poor wind conditions, return to base, emergency maneuvers, among other situations.

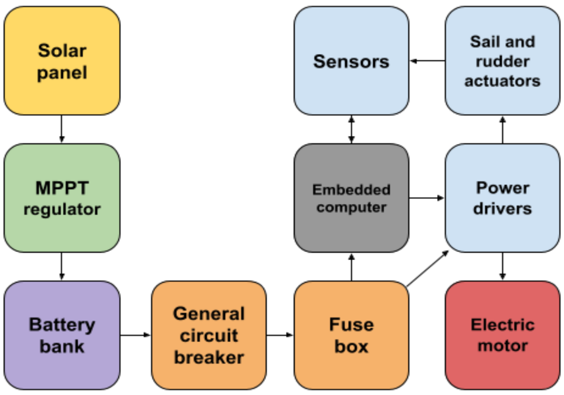

Figure 6. F-boat's current energy generation model

Our model uses a solar panel for the electricity production. In the future there is the possibility of using wind power generation and/or a mini hydro generator. Solar production has some advantages and disadvantages. The main advantage is that it corresponds to the most efficient in terms of cost, generation, extreme weather conditions resistance and ease of installation. However, there are lacks of moments where there is no source, such as night time or bad weather conditions. Another drawback is the large deck area required.

In the present project, we adopted a panel with the current-voltage graph shown in Figure 7.

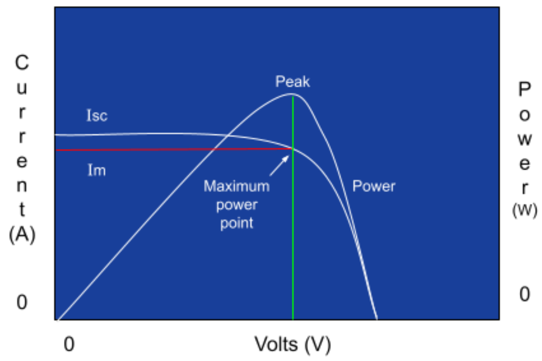

Figure 7. Current × Voltage curve for a photovoltaic panel.

The generation of electrical energy in a photovoltaic arrangement is intermittent and is strongly influenced by cloudiness and temperature. These factors cause the operating point that leads to the extraction of maximum power from the photovoltaic array to change constantly. Thus, tracking this Maximum Power Point (MPP) continuous is a way to ensure greater efficiency in energy conversion, as can be seen in the figure Figure 7.

To control the battery charge, a charger controller is necessary. This equipment can find the perfect current and voltage ratio that will charge the battery bank with maximum efficiency.

PWM, which stands for Pulse Width Modulation, is a charger controller that keeps a battery at full charge through high-frequency voltage pulses. Thus, this driver allows to check the battery charge status and adjust the pulses that are sent. This type is more used in the market as it has a lower price than an MPPT driver.

MPPT stands for maximum power point tracking and is a charger controller that looks for the maximum power point of the module or solar panel. This allows the system to make the most of the power the panel has to offer and also has an ability to monitor energy production and reduce system losses. This type of driver is more expensive than the previous one, but it promotes greater efficiency than the PWM controller.

In Figure Figure 8, it is possible to see a schematic diagram that reflects an alternative configuration on the N-Boat and F-Boat. For reasons of energy efficiency, the MPPT load driver is directly connected to the power distribution. As the electronic arrangement was designed with maximum system robustness and reliability, a power output is connected directly from the battery bank, being much safer than installing through the charge controller mentioned beforehand. Therefore, the boat can still be powered by the battery bank with a remaining charge. Here we also mention the necessity of using a general circuit breaker and a fuse box (with one for each compartment) guaranteeing maximum safety.

4.2 Electric and Electronic Components

In Figure 9 it is possible to visualize the F-Boat packages diagram. It features all of the vehicle's electrical and electronic components in a structured way, including also related documents, classes, diagrams and packages. Each package is better described below.

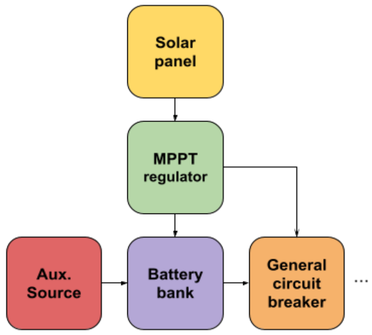

Figure 8. MPPT regulator connected directly to power distribution

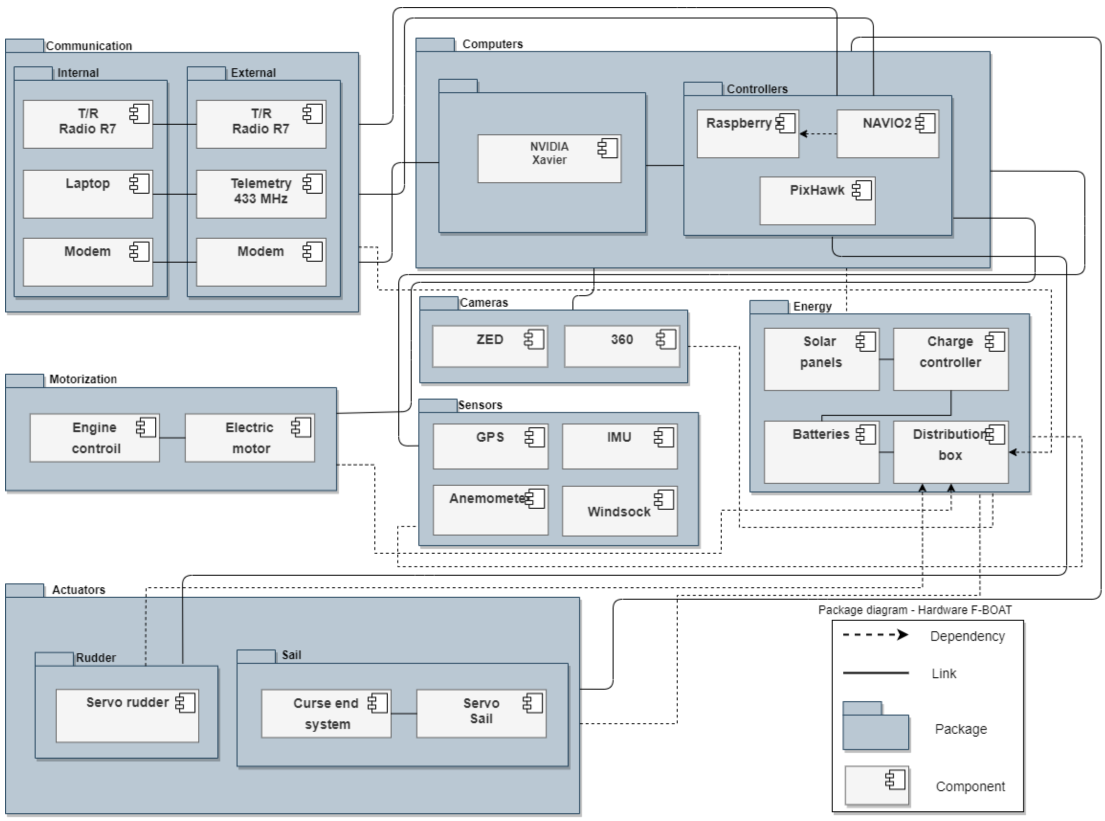

Figure 9. F-Boat's package flow diagram.

The energy package, which is the main focus of this work, contains the entire set of equipment responsible for the generation, storage and distribution of energy throughout the vessel. The sail package contains the components responsible for controlling the sail angular position and the rudder, as its name suggests, involves the components responsible for controlling the vessel's rudder. Computers are the devices responsible for all planning and data processing on the vessel. The communication package contains all components related to both internal (between all internal components of the sailboat) and external (communication with the shore base) communication. Motorization package relates all necessary hardware to the motorization of the sailboat, used in specific situations. Sensors are responsible for capturing the necessary data for both monitoring and general movement of the sailboat, working together with the cameras that are used for image acquisition, responsible for the computer vision tasks of the vessel.

4.3 System Consumption

Using solar panels, the production is enough to keep the sailboat system working without lack of energy. Of course, without using the electric propulsion motor. The Boltzman machine will actually be used for days when there is no full sunlight and/or massive use of the electric propulsion is required. In these cases, the boat will need to turn off some modules and behaviors for it to survive these moments. This same strategy could be used to further increase their autonomy, if necessary, as will be described later in this work.

As each battery has 111A/h, and the boat has 4 batteries of these on-board, the total energy available is 444 A/h. What in practice may represent lower values, as these batteries may not be 100% charged or addicted. Anyway, we use these values for simulation calculations.

Table 2 shows the components expected energy consumption, which is informed by the datasheet or by laboratorial tests carried out in previous experiments. Notice that, in the table some of the items are labeled as fixed or variable. This is due to the fact that some of them stay turned on throughout the entire mission, so their consumption is often identical to reported in the datasheet. However, other components have a consumption relative to their use. Such as the sail winch, which is only used when it is necessary to trim the sail. Taking into account the minutes that were turned on and relating it to the total consumption hour, so that it is possible to estimate an initial of the vessel's total energy consumption.

Table 2. Calculated energy consumption.

Nº	Description	Fixed/Variable	Consumption
1	Hardware	Fixed	2.0 A/h
2	Sensors	Fixed	0.2 A/h
3	Actuators	Fixed	0.9 A/h
4	Cameras	Fixed	1.0 A/h
5	Outboard engine	Variable	30.0 A/h
6	Sail winch	Variable	3.0 A/h

5 ENERGY MANAGEMENT EXPERIMENTS WITH RBM

Even sailboats that use wind as its main source of energy for its movement, electrical energy is still needed for its other components. As the production and storage of this energy resource is limited and scarce. Therefore, a system that distributes energy efficiently and safely inside the vehicle is needed. Besides, a strategy is essential to make intelligent use of this resource. With that in mind, the vessel was designed so that it was possible to make severe use of the battery banks for 48 hours without completely discharging and with being recharged by the solar panels.

That alone enables an ability to perform long missions. For so, protocols and consumption strategies were programmed, checking this energy consumption process. For example, on a given mission, it is possible to stay closer to the theoretical route, at a higher energy cost. However, few maneuvers reduced the sailboat consumption, but the actual accuracy on the theoretical route would also decrease. Another example would be to make little use of image processing in certain open sea locations. Leaving this feature to places with already pre-mapped obstacles or in places full of ships traffic.

In addition to this embedded technology, all of this raw and processed data is sent to a command base ashore or a nearby support vessel. These data are displayed via a user-friendly platform that allows data tracking, route changes, strategy changes and manual control of the sailboat for extreme situations. In the next section we will discuss energy use and further these exemplified strategies.

Application of solar panels systems for ships depends on many factors mainly: (i) Solar radiation availability in ship's operation areas, (ii) Existence of sufficient and adequate deck area to accommodate the solar panels, and (iii) Techno-economic efficiency of solar panels system: energy efficiency, fuel oil rates and investment costs.

In order to simulate the behavior of the system for the F-Boat, we implemented and tested through a Boltzman Machine using data collected from the electrical and electronic components of the N-Boat hardware architecture, such as described above. The implemented system aims to show a solution with the goal of finding a better way to use the distribution of energy consumption with solar panels in our autonomous sailboat with a saver engine. Through sensors and data obtained directly from the charge controller, the proposed system monitors and manages component power control through a relay system. The system also connects to two modules: computers, where it can change the energy operation of some of its components depending on the current state of charging the batteries, and to the vessel's communication package, which can send data to the external monitoring application.

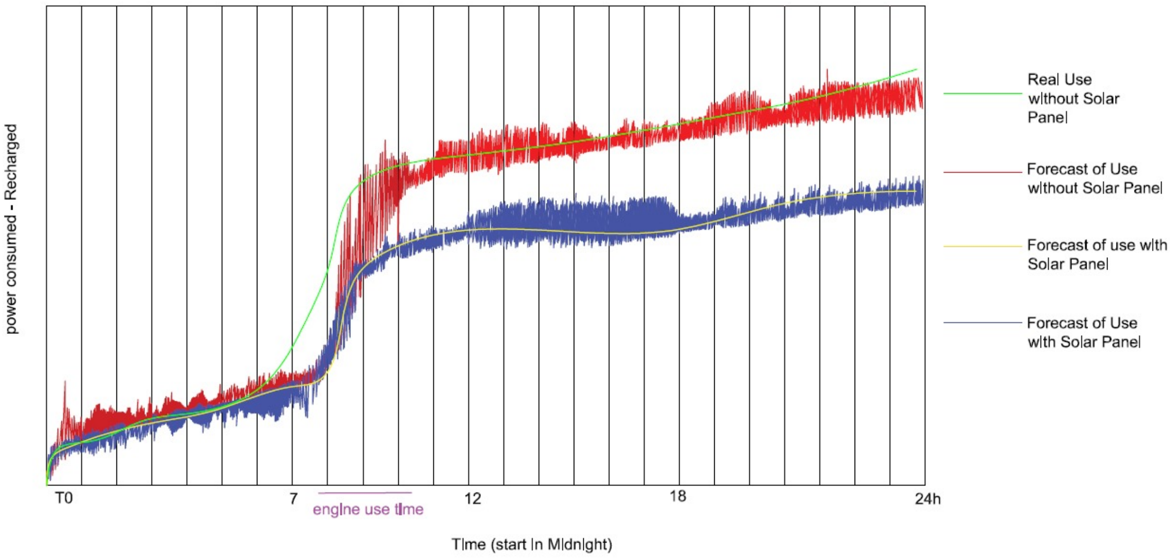

Figure 10. Results for estimated consumption of the sailboat on a 24 hours duration simulation, with data extracted from the N-Boat

We use the Boltzmann machine neural network with restrictions to predict the vessel's energy consumption in the 24 hour range. For this forecast, we designed the network to read data provided by sensors on the vessel itself, thus using external natural phenomena, winds, tides, lighting density, angle of incidence of sunlight. As navigation aids, we can predict the vessel's energy consumption with and without the use of solar panels.

The Restricted Boltzmann machine neural network is fully developed using Anaconda, Spyder 5 platform which is an open source cross-platform integrated development environment for scientific programming in the Python language. This development is aided by Numpy, Keras, Thensorflow and sklearne libraries which are open source neural network libraries written in Python. They are capable of running on the top of TensorFlow, Microsoft Cognitive Toolkit, R, Theano, or PlaidML. These tools are designed to allow quick experimentation with deep neural networks, focusing on being easy to use, modular and extensible.

Hence, we implemented a neural network code using standardized techniques to facilitate the learning process of the network. It has an initial layer with 6 neurons that receive as input tide data, wind speed and direction, vessel battery voltage, average motor consumption and consumption of the actuators. After normalization, we get 55 neurons in visible units and more 55 neurons in hidden units, connected similarly to the network presented in Figure 4, which process the data in 7 hours and 28 minutes with 4,903 iterations of epochs. As result, we obtain an estimated consumption of the vessel in the range of 24 hours. The graph in Figure 10 shows the generated results. These results found by the neural network are put in the test with real consumption values provided by the sensors of the vessel.

6 CONCLUSION AND FUTURE WORK

We validated our Boltzman Machine proposal for our autonomous sailing boats projects and achieved expected responses. In this sense, the association between renewable and continuous energy generation with an energy management strategy using the Boltzman machine resulted positively and is possible to conclude that artificial intelligence monitoring can suggest decisions such as sail movement, the best path to the target and the correct start and stop times for the electric propulsion engine

The results obtained in the simulation using the Boltzman machine showed strong evidence of a solution to the intelligent energy use problem in the sailboat. Anyway, a series of future work is planned to be done in this project, in order to improve the current work, such as the introduction of other forms of sustainable energy generation (wind and hydro generation), system monitoring through specific sensors for the entire solar panels, providing more precise information related to charge rate, battery bank charge, battery temperature, charge controller errors, etc. Still, a more effective survey of component energy consumption through bench and field testing in various work modes is required.

CONFLICT OF INTEREST STATEMENT

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

AUTHOR CONTRIBUTIONS

All authors have made substantial contributions to the conception or design of the work; the analysis, acquisition, and assembly of material and equipment; drafted the work and revised it critically for important intellectual content; and approved the version to be submitted, as described next. **AMPF**: Conceptualization, Methodology, Formal analysis and investigation, Writing - original draft preparation; **WSC**: Conceptualization, Methodology, Formal analysis and investigation, Writing - original draft preparation; **APDA**: Conceptualization, Methodology, Formal analysis and investigation, Writing - original draft preparation; **DHS**: Conceptualization, Methodology, Formal analysis, Writing - original draft preparation; **JMVB**: Conceptualization, Methodology, Writing - review and editing, Supervision; **DHND**: Conceptualization, Methodology, Formal analysis and investigation, Writing - original draft preparation, Funding acquisition, Resources, Supervision; **EWGC**: Conceptualization, Methodology, Formal analysis and investigation, Writing - original draft preparation, Writing - review and editing, Funding acquisition, Resources, Supervision; **LMGG**: Conceptualization, Methodology, Formal analysis and investigation, Writing - original draft preparation, Writing - review and editing, Funding acquisition, Resources, Supervision. In addition, all authors agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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SUPPLEMENTAL DATA

There are no supplementary data or material for this work, or resulting from this work.

DATA AVAILABILITY STATEMENT

Data and design materials produced from or for this study can be requested to the corresponding author by e-mail.

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