Energy Management in Autonomous Vessels Using Restricted Boltzmann Machine

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Abstract— **The management of energy in autonomous vehicles is an essential part to guarantee their autonomy and longevity, especially in autonomous sailboats. In this work we propose a methodology for the application of the Restricted Boltzmann Machine (RBM) neural network that aims to find a better way to use the distribution of energy consumption with solar panels in an autonomous sailboat equipped with a reserve electrical engine. The RBM receives input data from sensors coupled to the vessel and the output is an estimate of the overall dynamic energy consumption. We carried out an experiment using data from a vessel similar to the F-Boat that navigate and collect data in a region of lagoons in Rio Grande do Norte. The results show that it is possible to increase the level of confidence in the remaining stored energy and potential energy generation in the near future using this approach.**

I. Introduction

Energy performance is a very important issue to be considered when developing autonomous vehicles [1]. These vehicles normally have embedded hardware systems with specific purposes in which restriction of resources applies, both computationally and physically [2]. Another point to be considered is energy availability, which is limited, in the general sense. Hence, in most fully autonomous vehicles, mainly the ones used in long term missions, some clean power generation system such as wind or solar are generally embarked in order to generate the necessary power [3]. These systems capacity is normally greater than just the necessary power for some instant operation. Thus, some storage of the extra energy in batteries is done for future use or for example in the case of no energy production due to some reason (during the night, absence of wind for sailboats, emergency maneuvers). Optimizing the energy performance and reducing the operation cost can be done by way of some energy management strategy [4], [5], [6], [7]. Regardless the adopted approach, the correct energy management of all components should be implemented to prevent the complete use and discharging of energy resources, thus causing an energy failure in the entire system.

The vehicle used here is a sailboat, which is inspired by similar projects N-Boat I [8] and N-Boat II [9], whose main objective is the development of an autonomous sailboat to collect environmental data. Those projects have full documentation and pictures available at the web, in several sites [10]. In the same direction, our motivation for using a sailboat USV powered by wind instead of an electric-powered USV (or even using combustion engines) is that they provide greater autonomy [9]. This type of USV allows operation in long duration missions with a lower energy cost than the motorized ones, which are limited by the energy/fuel stored in its batteries/fuel tanks and subject to stoppages at refueling points during the mission.

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

Hence, in this project we borrow part of the solutions already used in the versions I and II of N-Boat, modernizing them with several enhancements or even re-implementing the hardware using the latest technologies. A completely new boat has been designed and built as seen in Figure 1. The sailboat movements are autonomously calculated and

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fully supported by data obtained from sensors and cameras. Although the propulsion is mostly made by wind, the project includes an electric motor for emergency or complex maneuvers. A series of sensors are embarked on the sailboat and their operation and integration are essential for the movement control and payload data collection by the sailboat. Robotics vision hardware intends to detect and classify objects on the environment and to take decisions from this. We propose that captured data should be stored or sent to a base station using telemetry for further analysis.

Nevertheless, the project construction still has several challenges to be overcome. One of the main ones, introduced above and treated in this paper, is that the sailboat must generate and manage its energy for long periods of time. We chosen to have the energy generated through solar panels and stored in batteries, in a scheme known as *offgrid*. The energy is used to power all the vessel's hardware, such as moving the rudder, sail and, when necessary, to drive an auxiliary electric motor. Towards solving the energy problem, in this work we propose a system including an energy optimization approach for the unmanned surface vehicles (USV). Our proposed system is able to automatically manage the generation system, distribution and configuration of components depending on the current state of energy storage. We propose here a set of rules that are implemented for emergency cases implemented by way of using a Boltzman Machine [11], [12]. Thus, with this contribution in mind, we start next describing some theory on the Boltzman machine used here and describing its energy generation system, further.

II. Restricted Boltzmann Machine

A Boltzmann Machine (BM) also called stochastic Hopfield network with hidden units or Sherrington–Kirkpatrick model with external field. The BM is a Markov random field and it was originated in statistical physics for use in cognitive science. The Boltzmann machine is based on a stochastic spin-glass model with an external field, i.e., a Sherrington–Kirkpatrick model that is a stochastic and it is suitable for some applications of Machine Learning [11], [12].

Boltzmann machines are theoretically intriguing because of the locality and Hebbian nature of their training algorithm, being trained by Hebb's rule, and also because of their parallelism and the resemblance of their dynamics to simple physical processes. Boltzmann machines with unconstrained connectivity have not proven to be useful for practical problems in machine learning or inference at all, but if the connectivity is properly constrained, the learning can be made efficiently enough to be useful in practical problems, more specifically for short predictions of states related to disjoint sensors data. These kinds of networks are named after the Boltzmann distribution in statistical mechanics, which is used in their sampling function. This is the reason why they are called *energy based models* (EBM). They are heavily popularized and promoted by pioneers in the cognitive sciences community and in machine learning [11].

More specifically, a Boltzmann machine, like a Hopfield network, is a network of units (Figure 2) with an ”energy”, in the Hamiltonian sense, defined for the overall network. Its units produce binary results. Unlike Hopfield nets, Boltzmann machine units are stochastic. The global energy in a Boltzmann machine is identical in form to that of Hopfield networks and Ising models:

$$E = -\left(\sum_{i<j} W_{ij} S_i S_j + \sum_i \theta_i S_i\right) \tag{1}$$

Theoretically the Boltzmann machine is a rather general computational medium. For instance, if trained on photographs, the machine would theoretically model the statistical distribution of photographs, and could use that model to, for example, complete a partial photograph.

Unfortunately, Boltzmann machines experience a serious practical problem, namely that it seems to stop learning correctly when the machine is scaled up to anything larger than a trivial size. This is mainly due to the fact that the required time order to collect equilibrium statistics grows exponentially with the machine's size, and with the magnitude of the connection strengths. These connections strengths are more plastic when the connected units have activation probabilities intermediate between zero and one, leading to a so-called variance trap. The net effect is that noise causes the connection strengths to follow a random walk until the activations saturate.

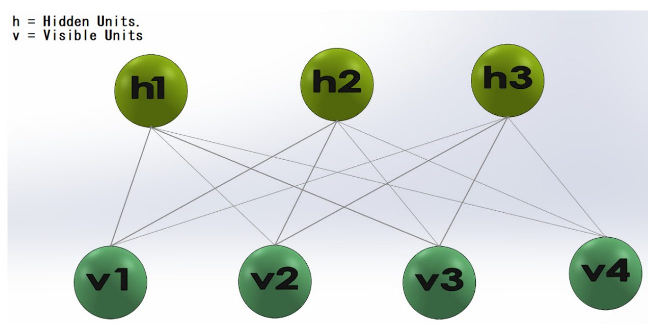

Fig. 2. A simple Restricted Boltzmann Machine architecture.

This learning rule is biologically plausible because the only information needed to change the weights is provided by ”local” information. That is, the connection (synapse, biologically) does not need information about anything other than the two neurons it connects. This is more biologically realistic than the information needed by a connection in many other neural network training algorithms, such as backpropagation. The training of a Boltzmann machine does not use the Expectation-Maximization (EM) algorithm, which is heavily used in machine learning. By minimizing the KL-divergence, it is equivalent to maximizing the log-likelihood of the data. Therefore, the training procedure performs gradient ascent on the log-likelihood of the observed data. This is in contrast to the EM algorithm, where the posterior distribution of the hidden nodes must be calculated before the maximization of the expected value of the complete data likelihood during the M-step.

III. Power Generation System

The sailboat's energy generation system uses solar panels with a charge controller and batteries, to provide constant energy charge during its missions. According to the literature [13] the energy generated is enough for control of the sail and rudder (with wind propulsion of the vessel) in the case of a single hull, as is the case of F-Boat, also including power for the electronic devices embarked and some eventual payload application. Hence, F-Boat starts using this simpler power plant, however with an architecture that allows to implement an alternative approach that has been thought, which is the development of a way to recharge off-grid batteries, aiming to directly contributing to the activation of its electrical propeller at any time. In this case, although being secondary, the electrical motor assumes the main vessel propeller system for a small amount of time, as far as continuous power generation is possible and a specific maneauver is required. The sail is also used together and the result is a system that works integrated, increasing energy autonomy with a hybrid propulsion model, increasing the sailboat's maneuverability and decreasing its reliance on the wind situation.

A. Energy generation approaches

Several configurations can be seen in Figure 3, which shows a detailed description of the necessary steps for including new methods for energy generation. The initial option is the photovoltaic panel to recharge the main batteries. Following this approach, Figure 4 shows the diagram items of the modular autonomous and renewable energy-power project of F-Boat.

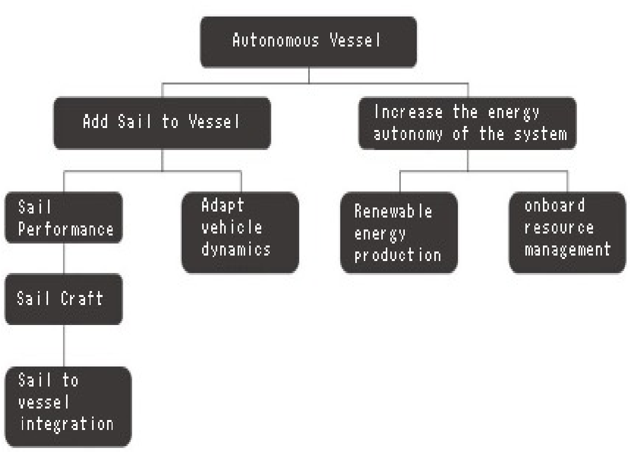

Fig. 3. Energy generation approaches.

There are some main advantages of using a solar panel to capture energy. It does not consume fuel so does not produce pollution or environmental contamination. It is silent. It has a useful life of more than 20 years being resistant to extreme weather conditions (hail, wind, temperature and humidity). It has no moving parts and therefore requires little maintenance (only panel cleaning) and allows to increase the installed power through the incorporation of additional modules. There are also some limitations such its weight, occupancy space, and the need for positioning in such a way that it gets direct impact from solar rays.

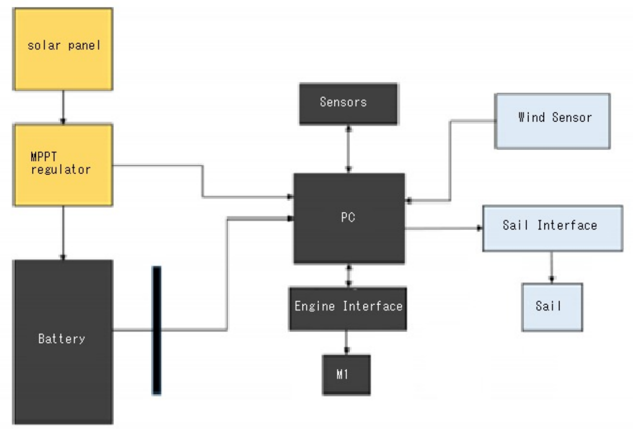

Fig. 4. F-Boat renewable power generation modules.

One of the recent technological novelty is the flexible solar panels, which can be mounted on curved or arched surfaces, being 70% lighter than crystalline panels. They are about 2 millimeters thick, thus producing less wind noise, and are resistant to salt water. Compared to conventional rigid panels, the performance is considerably higher. We chose the panel from the manufacturer SUNLOAD with 21 Wp with 995x330x2 mm, with a weight of 750 grams, which perfectly meets the requirements described above. With the dimensions of this solution, the panel can be placed on the hull without deforming the sailboat hull's aerodynamics, as the panel is flexible and conformable to the appearance of the deck. However, as each cell produces a reduced electrical power, the cells are interconnected to form a photovoltaic mosaic. Figure 5 shows the current-voltage curve graph (I-V curve) of the photovoltaic panel output.

Through the characteristic curve of the panel we can observe that the maximum achieved power does not correspond to the individual maximums of voltage and current, but to the point where the product of current and voltage is maximum. This maximum power point (MPP) varies with environmental conditions, specifically according to temperature and incidence of solar radiation. Thus, there are several different modes of operation for solar panels, making it necessary to find out which configuration is adopted for the photovoltaic panels and batteries. That is, it must be determined if the panels connect directly to the batteries, serving only to charge them or if they are connected to the engines and batteries through a switch. Notice that this mode allows the vessel propulsion to be activated directly in the case of emergency situations, as shown in Figures 6 and 7.

Note that the first model has the advantage of greater

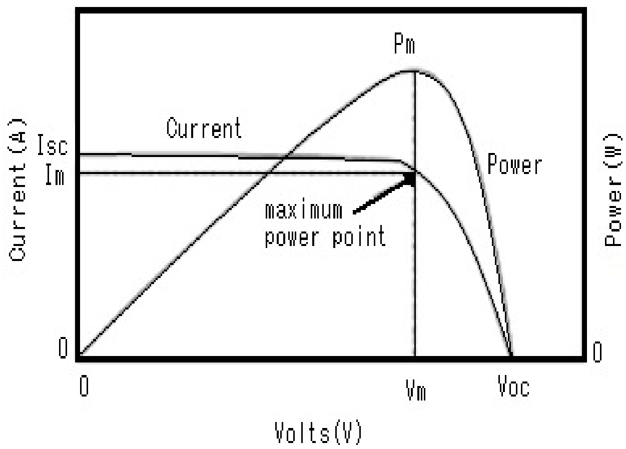

Fig. 5. Current × Voltage curve for a photovoltaic panel.

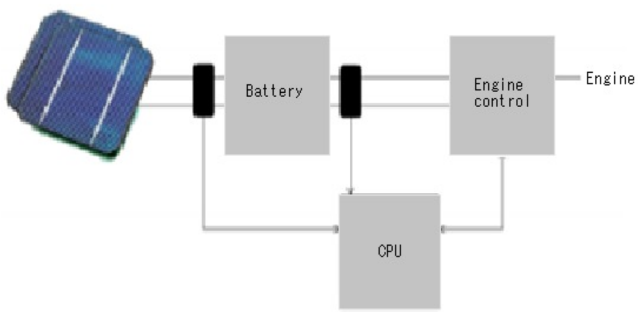

Fig. 6. Panels connected in series directly to the battery.

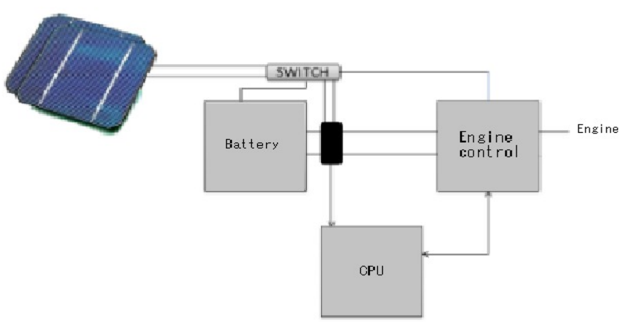

Fig. 7. Panels connected in series to batteries and motors via a switch.

simplicity of implementation. However, it needs some more electronic material to make the connection between the panels and the batteries. The second model has the advantage of having a control interface that allows the photo-voltaic panels to either charge the batteries or directly drive the motors. This last control method is interesting to be used, for example, in emergency situations. However, this greater robustness of the panels translates into their greater control complexity. That is, photo-voltaic panels must be optimized to always extract the maximum power possible. As seen, the maximum power point of a panel depends on several factors, including radiation and temperature. To solve this problem, we use the method known as *Maximum Power Point Tracking* (MPPT) to get its maximum power point at every instant that the panel operates. The MPPT control aims to guide the operation of the converter in order to extract, at every moment, the greatest possible power.

B. Electric and Electronic Components

Figure 8 presents the F-Boat packages diagram for its electric and electronic components. Package diagrams are known to be structural diagrams that are used to introduce, in a packaged form, the organization and arrangement of the several components of a model. In practice, a package is a group of components that relates to each other such as diagrams, documents, classes or even other packages [14]. It can be noticed that new modules or components can be inserted or removed during the project creation. Each package is better described in the next.

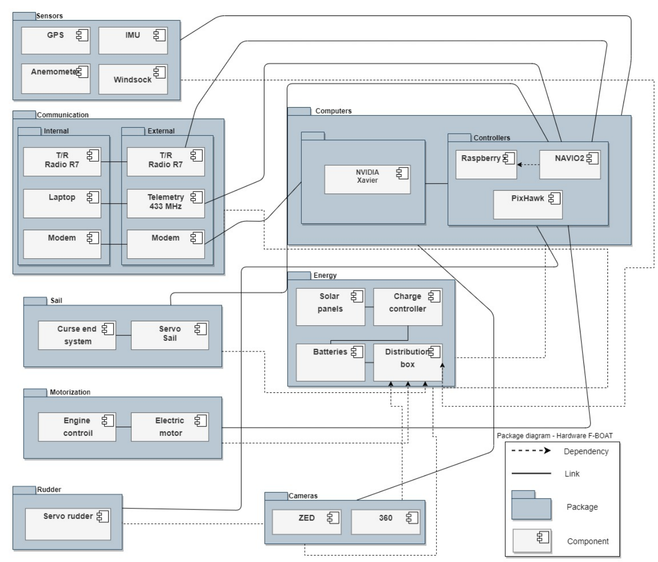

Fig. 8. F-Boat's package flow diagram.

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. 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. Motorization package relates all necessary hardware to the motorization of the sailboat, used in specific cases. Computers are the devices responsible for all planning and data processing on the vessel. 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 part of the vessel. The energy package, which is the main element of this work, contains the entire set of equipment responsible for the generation, storage and distribution of energy throughout the vessel.

C. System Consumption

Table I shows the expected energy consumption of the system components, which is calculated based on the electric and electronic components data sheets. With the addition of the solar panels we expect to have a production that is enough for supporting the system. The Boltzman machine can be used just to infer if the generated power is enough, and, if not, what are the components that eventually can be shut down in order for the sailboat to survive. Also, strategies for augmenting the sailboat autonomy can be derived using it, as it will be shown in the experiments that we performed. We notice the use of four batteries here, each one giving approximately 111 A/h. So the total power of 444 A/h is expected, overall, with the batteries only.

Table I shows the individual hourly consumption of each of the general systems and components of the vessel, considering that the systems with the fixed brand are those that remained on during the entire navigation period of the vessel and those with variable marking will be used under special conditions or sporadically. The punctual consumption of these items is calculated with better accuracy, taking into account the minutes that were turned on and relating it to the total consumption hour, so we can have an initial estimate of the vessel's total energy consumption. Considering this, we can say that the fixed consumption is 4.1 A/h and the variable is determined at the instant that the motor or winch starts operating.

TABLE I
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

D. System Management

As the sailboat will produce and store its own energy through solar panels and batteries, a distribution and control system for this energy must be implemented. This system must be able to autonomously perform several tasks as: real-time monitoring of both charging and energy storage conditions of the system; definition of energy consumption protocols for vehicle operation; enable or disable the functioning of components; change, if necessary, the operating mode of components; and apply emergency protocol if necessary.

Besides the above tasks, all settings and information obtained must be accessed by the ground crew through a friendly graphical interface, where the user will be able to visualize the consumption of each component and adjust its operating parameters. The experiments in the following are part of this system that determines whether the energy is sufficient or which components should be turned off in order for the system operates in a safe way. All of the above tasks of the management system can rely on the results of this network.

IV. Experimenting with Restricted Boltzman Machine

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 system 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.

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 write 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 Figure 2, that 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 9 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.

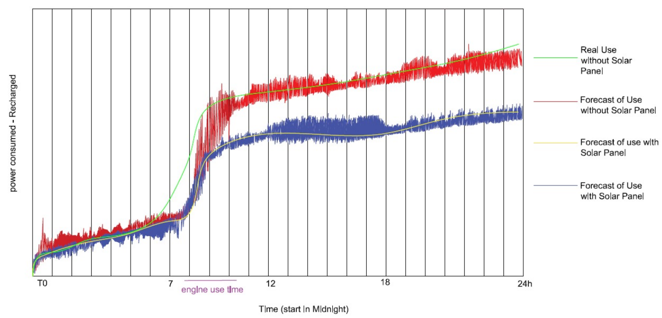

Fig. 9. Results for estimated consumption of the sailboat on a 24 hours running on simulation, with data extracted from the N-Boat

V. Conclusion and Future Work

With basis on the performed experiments and their evaluations, we realize that it is possible to create a tool capable of managing the total energy plant of the sailboat. This embedded energy management control system can monitor and take eventual decisions for a better energy performance, based on data provided by the Boltzman machine. With an artificial intelligence, the monitoring can be done, including decisions as sail motion, the best path to target, and the correct saver engine start and stop times. In the very short, we will develop a system to make local forecasts of weather conditions, future forecasts of currents and tides, estimation of mission success along the route, performance optimization by energy source by micro-grids.

There are a series of future works to be done in order to enhance the current architecture. One of them is the development of a supervisory (monitoring) system through specific sensors. The entire solar system can be monitored, bringing information such as: charging rate, battery bank charge, battery temperature, errors from the charge controller, etc. Still, there is a lack of a more effective survey of the energy consumption of the components through bench tests in various work modes. The implementation of switching and monitoring the power outputs of all components/modules is the next step after that, with the definition of a minimum set of components that are considered vital for the operation and control of the vessel. The implementation of different energy profiles must be completed, with the inclusion of an emergency system used only in specific cases, such as problems in the energy generation system or even batteries at critical charging levels. Finally, there is also a need to develop an application for real-time visualization of data relating to the entire energy system. Through the application it should also be possible to change configurations relating to the system.

Acknowledgments

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