Artificial Endocrine Controller for Power Management in Robotic Systems

Colin Sauzé and Mark Neal

Abstract—**The robots that operate autonomously for extended periods in remote environments are often limited to gather only small amounts of power through photovoltaic solar panels. Such limited power budgets make power management critical to the success of the robot's mission. Artificial endocrine controllers, inspired by the mammalian endocrine system, have shown potential as a method for managing competing demands, gradually switching between behaviors, synchronizing behavior with external events, and maintaining a stable internal state of the robot. This paper reports the results obtained using these methods to manage power in an autonomous sailing robot. Artificial neural networks are used for sail and rudder control, while an artificial endocrine controller modulates the magnitude of actuator movements in response to battery or sunlight levels. Experiments are performed both in simulation and using a real robot. In simulation a 13-fold reduction in median power consumption is achieved; in the robot this is reduced to a twofold reduction because of the limitations of the simulation model. Additional simulations of a long term mission demonstrate the controller's ability to make gradual behavioral transitions and to synchronize behaviors with diurnal and seasonal changes in sunlight levels.**

Index Terms—**Artificial endocrine controller, neural networks, power management, robotics.**

I. Introduction

THIS paper describes the application of an artificial endocrine controller for power management within robotic systems. The endocrine system is an intercellular communication system, which operates by secreting chemical messengers known as hormones into the bloodstream. Hormones travel throughout the body in the bloodstream and bind with receptors on target cells. Upon binding they trigger a behavioral change within the target cell. Hormones are responsible for regulating a number of parameters, which keep the body within a stable state in which life can continue. Examples of parameters regulated by the endocrine system include blood sugar, body temperature, blood pressure, salt levels, and the duration and timing of sleep. The endocrine system also exerts influence over the behavior of the neural and immune systems. Reproducing such properties in a robot could improve its ability to adapt its behavior to deal with a changing internal state. An artificial endocrine system applied to power management problems would allow a robot to adjust its behavior depending on the amount of energy available to it. This could be applied both to energy levels over a period of minutes, hours, or days in response to fluctuating power generation and to longer term degradation of components, which could affect the robot's ability to produce power or increase its power consumption. A number of endocrine inspired approaches have been developed and applied to abstract simulations or short-term laboratory robot experiments; however, there has not been any major consideration of longer term situations. Through the use of more intelligent methods of power management it may be possible to operate such robots for longer, using smaller energy reserves or smaller and simpler power generation systems. Ultimately this can facilitate increased autonomy and flexibility and/or reduced costs in operating robots in harsh environments with little or no human supervision.

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The authors are with the Department of Computer Science, Aberystwyth University, Ceredigion SY23 3DB, U.K. (e-mail: cos@aber.ac.uk; mjn@aber.ac.uk).

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II. Background

A range of benefits can arise from artificial endocrine controllers [1]. This section outlines work in five areas where artificial endocrine controllers may be beneficial to autonomous robots operating over long periods in harsh and remote environments. These are: 1) maintaining a stable state; 2) action selection and gradual state switching; 3) balancing competing demands; 4) exploiting opportunities; and 5) synchronizing behavior with the external environment.

A. Maintaining a Stable State

Homeostasis is the biological process in which various parameters are maintained within an equilibrium and regulated within set limits through a series of negative feedback mechanisms. The endocrine system is a key to this, with a common example being the regulation of blood sugar levels with insulin and glucagon. These hormones vary the level of glucose taken up by cells and trigger the liver to convert glycogen stored in fat cells into glucose which can be used by other cells. Artificial homeostasis attempts to perform a similar task within an artificial system such as a robot. Potential examples might include regulating the temperature of the robots components or managing power consumption to prevent a battery from completely discharging.

Perhaps the earliest example of an artificial homeostatic system is Ashby's Homeostat [2], a mechanical system that attempts to keep several electromagnets connected to pivots in a stable position while the electrical connections and voltage levels driving them are varied. More recent work by

Arkin [3], [4] produced robot control systems, which adapt the robot's behavior in response to fuel levels and internal temperature. Moioli *et al.* [5] later developed a more sophisticated system based around an artificial neural and endocrine system which attempted to maintain the charge state of a battery. In further work [6], they developed a controller, which was able to adapt to other forms of disruption in the robot's environment. Cañamero and Garcia [7] noted that the robot must be maintained within a zone of viability to continue operation, but that simply staying within the zone of viability is not optimal. Instead they stated that the robot should aim to achieve a quality of life by trying to maintain itself well within the viability zone, rather than oscillating around its boundaries. They developed a hormone inspired system which responded to the robot's comfort level with respect to temperature and energy levels.

B. Action Selection and Gradual State Switching

Artificial hormonal control can be used as a mechanism for action selection in robotics. Hormonal signals can be used to both activate and inhibit an activity. A number of different approaches are taken to apply this analogy in robotic systems. In [7]–[11], and [12]–[14], hormones were used to signal the activation or deactivation of a behavior when a hormone reached a threshold. This created an action selection mechanism based on a winner takes all approach where only one behavior would be selected at any time. An alternative to this approach proposed by Neal and Timmis [15] allows multiple behaviors to be simultaneously active, by encoding each behavior as a neural network and modulating the output of the network via hormone levels. This allows individual neural networks to gradually be promoted or suppressed by an artificial endocrine controller, creating the possibility of activating (perhaps only partially) multiple behaviors simultaneously. Gradual transitions between behaviors can be achieved, although rapid transition is still possible when required. In their initial work [15], a neural network exhibiting a wander behavior on a mobile robot was modulated to panic when the robot became trapped or surrounded. In an extension of this paper [16], switching between eight different behaviors was achieved using a set of hormones.

A further refinement to endocrine action selection was taken in [17]. One neural network was trained to follow black objects and another to follow white objects. These networks were promoted and suppressed by a hormone with a sinusoidal oscillating concentration level. In this, system would often lose momentum and stabilize in an intermediate state in which neither color was sought. To overcome this, hormones are produced when a certain stimulus occurs, but stored in the pool until a threshold value is reached when the pool is emptied. This releases a surge of hormone, triggering a sudden behavioral change. The hormone then decays geometrically. This overcame the stagnation of the behavior switching allowing the robot to oscillate between seeking the black and white objects. Walker and Wilson [18] used such pooling hormones to switch between three behaviors using a winner takes all approach in which the behavior that had the highest hormone concentration was selected.

C. Balance Competing Demands

Through the gradual promotion and suppression of behavior it may be possible for a robotic system to balance competing demands. For example, one behavior, which is attempting to reduce power consumption, could be balanced against another, which is trying to prevent the robot from straying into danger. At times, the danger avoidance behavior may require the robot to perform high power maneuvers which will have to be balanced against the power saving behavior. This might be achieved by temporarily suppressing behaviors relating to longer term issues such as those controlling power consumption. Competing demands are likely to include the requirement to maintain the robot within a viable, homeostatically stable state. Attention may need to be paid to the amount of hysteresis in the system to prevent rapid oscillation around boundary conditions. Although many researchers have identified this as a potential application for artificial endocrine controllers, there does not appear to have been any work on this topic so far.

D. Exploiting Opportunities

Artificial endocrine controllers offer a potential mechanism for a robot to exploit unforeseen opportunities such as finding themselves with excessive amounts of energy or coming across an object of interest (e.g., a planetary exploration rover passes an interesting rock). Examples of such controllers include work by McFardland and Spier [19], in which simulated robots are able to obtain fuel from their environment, but must trade-off this against the need to continue performing other tasks. They discuss the need to exploit the opportunity of coming across fuel in the environment, even if there is no immediate need to refuel. This exact scenario may be unlikely to occur in the real world at present, as there are few current technologies which can exploit fuel deposits which a robot may encounter in exploring its world. A more realistic scenario is a robot powered by photovoltaic panels, which charge batteries during daylight hours: opportunism could exploit days, which are sunnier than average to perform additional tasks or to better position the robot, for example, a sailing robot could sail upwind or an airborne robot could gain altitude.

E. Synchronizing With the External Environment

Synchronizing behavior with external environmental variables, for example, cycles of the sun or tide enables the preemptive scheduling of tasks around environmental constraints. One potential source of inspiration is the hormone melatonin, which is often cited [20] as controlling the sleep cycles of mammals in response to exposure to sunlight. This could be applied to solar powered robots to control the scheduling of activities to coincide with the maximum availability of energy. Work in this field [21] demonstrated simulated organisms, which would only seek food during daylight as they cannot see or move during darkness.

Rocks and Barnes [22] adopted a similar idea using an artificial circadian rhythm based on the entrainment of an internal oscillator from external sunlight cues. This system allowed the robot to adapt to changes in the length of day caused by long distance travel or seasonal changes. The use of an internal biological clock also allowed the robot to maintain its sense of day and night even if it temporarily lost sight of any daylight. This was applied to a simulation of a Mars exploration rover and was used to schedule tasks around daily and seasonal solar cycles.

Although not a biologically inspired approach, Shillcutt and Whittaker [23] also demonstrated synchronization of robot behavior with the sun through the use of a solar synchronous vehicle. This vehicle circumnavigates a planet near the pole during summer, this allows it to remain in an optimal position in relation to the sun to generate the maximum amount of electricity.

F. Review Summary

It is clear that work in this area shows promise for power management in embodied robots in real unconstrained environments and provides a technique that is capable of dealing with environmental variations and cycles in a flexible and adaptive manner. The remainder of this paper describes one such approach used in a sailing robot.

III. Example Implementation of an Artificial Neuroendocrine Controller

This section presents an example implementation of an artificial neuroendocrine controller within the target application of modulating power consumption in an autonomous sailing robot. Such a robot presents an ideal candidate for a neuroendocrine controller when applied to the problem of power management and longevity. The envisaged robot is solar powered and must operate on a marginal power budget. As the availability of power will be highly variable and subject to seasonal trends, the ability to exploit excessively sunny days and to adjust behavior depending upon the season will be beneficial. Looking back to the areas outlined in the previous section, this example tries to maintain a stable state, perform gradual state switching, exploit opportunities, and synchronize with the environment.

A. Modifications to the Neuroendocrine Controller Architecture

Some modifications to the neuroendocrine controller architecture devised by Neal and Timmis in Section II-B are made to reduce complexity. Their work modified a traditional multilayered perceptron [24], [25] adding an artificial hormone gland which released a hormone that modified the behavior of the neural network. They took the traditional formula for calculating the output of a perceptron, which takes the sum of one or more inputs each of which is multiplied by a weight as follows:

$$\sum_{i=0}^{n} w_i x_i \tag{1}$$

where w is the weight assigned to a connection, x is the input value, and i is the input in question.

They then modified this formula to include modulation from a set of artificial hormones, as shown in

$$\sum_{i=0}^{nx} w_i x_i \prod_{j=0}^{ng} C_j S_{ij} M_{ij}. \tag{2}$$

These hormones are secreted by a set of artificial glands g. Each hormone specifies a concentration value C, this shows the quantity of the hormone that is available and is analogous to the concentration of the hormone in the bloodstream. Each neuron has a sensitivity level S to each hormone, this determines the size of the effect the hormone has upon the neuron in question. In biological systems, there are variable levels of matching between the target cell's receptors and the hormone. In the artificial system this is simulated with the variable M whose value is calculated in

$$M = \frac{1}{1 + dis(i, j)}. \tag{3}$$

The rate of hormone release is governed by the formula shown below in (4), where α_g is the rate at which hormone is released for a specific gland (g), x_i is the input to the gland, and n is the number of inputs to the gland

$$r_g = \alpha_g \sum_{i=0}^{nx} x_i. \tag{4}$$

In biological systems, the concentration of a hormone in the blood stream will gradually decay over time, assuming that no additional hormone is secreted by the gland which produces it. This decay is due to hormone molecules binding with receptors upon target cells. However, in an artificial system no such physical process is present to remove the hormone from the bloodstream. Therefore, the bloodstream hormone concentration must be artificially decayed over time. Neal and Timmis followed a simple geometric decay function as shown in

$$C(t+1)_g = C(t)_g \beta \tag{5}$$

where C is the hormone concentration, g specifies the gland in question, $C(t)_g$ specifies the bloodstream hormone concentration for a given point in time t, and β specifies a constant decay rate for the hormone.

The receptor matching distance, hormone concentration, and hormone sensitivity together control the level of behavioral change which will be seen in the neural network in the presence of a given hormone. As the receptor matching distance and hormone sensitivity both provide unchanging values they could be combined into a single number. By doing this we reduce the size of our parameter space. Therefore, a simplified formula for calculating the output of a single perceptron becomes

$$\sum_{i=0}^{n} w_i x_i C_j S_j \tag{6}$$

where w is the weight, x is the input value, C is the hormone concentration, and S is the hormone sensitivity. i is the current input from a set of neural network inputs and j is the current hormone from a set of hormones. This, however, encounters problems if C is zero, as the neural network will have a zero output. It would be more useful for the network to behave

TABLE I
SPECIFICATIONS OF THE MOOP SAILING ROBOT

Length	74cm
Draft	12.5cm
Beam	21cm
Weight	4kg
Sail	7cm x 30cm rigid wing sail
Power	55 Wh of NiMH batteries
Computers	Gumstix Single board computer and PIC 18F4550 Microcontroller
Communications	802.11 b/g wireless network
Sensors	SiRF III GPS, HMC6343 tilt compensated compass, AS5040 rotary encoder for wind sensor
Actuators	Servos for sail and rudder

normally when C is zero. Equation (7) adds one to S and C, to overcome this problem. Values of S are restricted between zero and one, with a zero causing the hormone to make no change and one the maximum level of change.

$$\sum_{i=0}^{n} w_i x_i (1 + C_j S_j). \tag{7}$$

In the Neal/Timmis system, hormone is released and decayed in a geometric fashion (shown in (4) and 5). To simplify this process and further reduce the number of variables in the system the hormone decay function is redesigned to incorporate a single variable for both. The release rate is determined by some kind of external stimulus. This gives the formula as follows:

$$C_{t+1} = C_t - r(C_t - q) \tag{8}$$

where q is the quantity of hormone being released and r is the decay/release rate.

B. Sailing Robots

The target robots for this paper are autonomous sailing robots, which are intended to spend months at sea performing autonomous oceanographic monitoring. For this paper, a pair of 74-cm-long Miniature Ocean Observation Platform (MOOP) [26] robots are used. These are inspired by a Nordic folk boat with the keel integral to the hull. They are propelled by a single wing sail that is positioned by a servo motor. Steering is provided by a servo in the stern which moves the rudder. Full specifications are shown in Table I and a photo of the boat is shown in Fig. 1. These boats are not equipped with solar panels, but it is calculated that 12 × 4.4 V, 90 mA (4.75 W peak) panels could be fitted on the deck. Assuming a solar panel is placed flat on the earth's surface (or flat on a stationary boat's deck) the power output will be proportional to the angle of incidence from the sun and the earth's surface, with the peak output only being seen when the sun is directly overhead [27]. On a winter day, the sun will be lower in the sky than a summer day and it will be visible for less time. On a cloudless day, at 52° north in June a 4.75 W peak panel will provide around 41 Wh of energy per day. At the equinox (March/September), it will provide around 23 Wh per day, and in December, it will only provide 5 Wh per day [28].

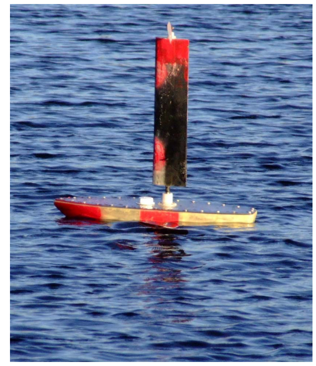

Fig. 1. Photograph of one of the MOOP sailing robots.

TABLE II
POWER CONSUMPTION, BATTERY CAPACITY, AND SOLAR PANEL FIGURES USED BY THE SIMULATOR

Name	Power
Batteries	55 Wh - equivalent to 20 AA NiMH rechargeable batteries (1.2 V, 2300 mAh each)
Solar Panels	4.75 W Peak, based on fitting 12x 4.4 V, 90 mA solar panels
Rudder Actuator	0.0003109 Wh per position (11 positions total, 18 degrees each) of actuator movement
Sail Actuators	0.00010594 Wh per position (11 positions total, 18 degrees each) of actuator movement

C. Robot Simulator

In addition, a simulator is implemented to allow algorithms to be tested before deploying them on the robots. As the simulator does not suffer from many of the hardware faults, deployment/recovery issues or the need for suitable weather or require travel to a test site, it is much easier to run large numbers of simulations than real robot tests. The simulator is based upon Tracksail,[1] an open source sailing game. This implements a basic physics model of a sailing boat and is modified to allow for autonomous control. The simulator does not simulate the actions of waves that a real robot would experience, nor does it accurately simulate shifts in the wind speed and direction. For the purpose of this paper, wind speed and direction are constant.

1) Simulation of Electrical Systems: Some additional modifications are made to the simulator to track the electrical power generation, storage, and consumption of the simulated robot. The figures for battery capacity, solar panel capabilities, and actuator power consumption are based upon those of the robots. The figures used are shown in Table II.

The output current of the solar panel is made proportional to the sine of the angle of the sun for the simulated time of day, it is assumed that the solar panels would be horizontal with no cloud. Sun elevation is calculated using the Solpos library[2] from the U.S. National Renewable Energy Laboratory. The battery level is recalculated during each iteration to consider the amount of power generated by the solar panel and used by the actuators. This is specified by the formula as

[1] http://tracksail.sourceforge.net
[2] http://rredc.nrel.gov/solar/codesandalgorithms/solpos/

follows:

$$b_{t+1} = s/3600 + b_t - c/3600 \tag{9}$$

where b is the remaining battery capacity in watt hours. s is the amount of power generated by the solar panel in watts and c is the power consumption of the actuators in watts during the current iteration of the simulator. The value for c is calculated by multiplying the distance moved by power consumption per position (as specified in Table II).

This model simplifies several aspects of the power consumption process as it assumes that 100% of the power which is collected by the solar panels is transferred into the battery and that the battery is able to return 100% of it at a later time. Actuators are always assumed to draw the same amount of power for each degree of movement, actuator load is not modeled and power consumption is assumed to be constant throughout the entire movement. As no power monitoring hardware is present in the boat (due to space and engineering constraints), the robot experiments also follow the same process for determining actuator power consumption.

D. Neural Network Setup

1) Neural Network Structure: Two separate, fully connected, three layer perceptrons are used as controllers for the rudder and sail. The sail controller takes as input the current sail actuator position and the wind direction and returns the change in sail actuator position (from its current position). The rudder controller takes as input the current rudder actuator position and the heading error (difference between the target heading and desired heading). It also returns the desired change in the rudder actuator position. As discussed in Section III-C.1, each actuator is a servo motor which rotates through 11 unique positions at 18° intervals. This interval is chosen as smaller intervals are not able to repetitively cause the actuator to actually move to a different position. Although the obvious design decision might be for the neural network to output an absolute actuator position, when applying inhibitory endocrine modulation this would cause the actuator to move toward a certain (presumably central) position. Instead, what is needed is a system that would suppress movement. Therefore, the decision is taken to output a relative actuator position instead of an absolute one. As there are only 11 unique positions, the output values from the neural network are rounded to the nearest of these.

Rudder training data is generated from a proportional controller, which is used during earlier development of a sailing robot control system. Sail training data is generated from a lookup table relating sail positions to wind directions. The network is trained using the backpropagation algorithm [29]. Initially two hidden nodes are used, but the network struggled to train acceptably and the hidden layer had to be increased to eight nodes before the network performed satisfactorily using test data. The value of the hormone and the endocrine controller is not considered during training and is felt to be beyond the scope of this paper.

In previous work by Neal and Timmis [15], modulation was applied to all nodes in the neural network, and other strategies by Henley and Barnes [30] applied hormonal modulation selectively to a few neurons. We found that applying modulation to all nodes of the network produced a nonlinear response between the hormone concentration and change to the output of the actuator position. Therefore, it is decided to only apply hormonal modulation to the weights of the neural network's output layer. A diagram illustrating the network layout and modulation strategy is shown in Fig. 2.

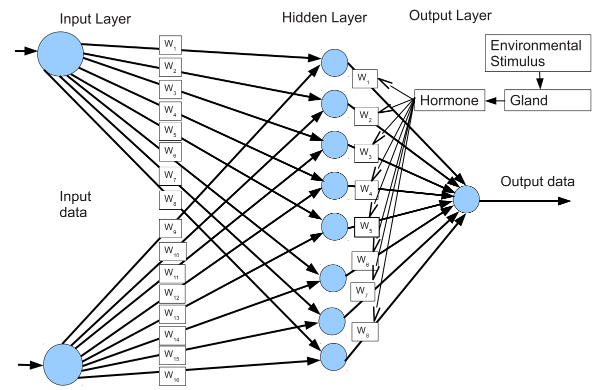

Fig. 2. Diagram showing the neural network structure and how it is modulated by a hormone.

IV. Simulator Experiments and Results

Four experiments are carried out to investigate how an artificial endocrine controller could manage the power consumption of a simulated sailing robot. The first experiment fixed the hormone levels for its entire duration, while the robot sailed a predefined course. This allowed us to assess the extent to which modulation can be applied before the robot became uncontrollable. The second experiment allowed the battery to discharge over the course of the experiment and measured how long the boat is able to sail for until the battery is discharged. The third experiment added a simulated solar panel, which could recharge the battery. The final experiment added a second hormone, which represented the level of sunlight. This suppresses control system actions during the night and promotes them during the day.

A. Fixed Hormone Level Simulations

To first test the effect of hormonal modulation on a sailing robot, a series of short courses is sailed with the hormone level and sensitivity fixed for the duration of each run.

The hormone used for this experiment is considered to be analogous to glucagon and insulin, and would suppress or promote actuator use in response to battery level. To calculate the hormone level a gland function producing the hormone used the formula as follows:

$$0.023b - 1.03 \tag{10}$$

where b is the amount of battery remaining in watt hours (between 0 and 55.2 Wh). The output level of the function should always be between -1.03 and 0.24. This slight positive output when the battery level is above approximately 44.8 Wh (about 82% of capacity) will have an excitory effect

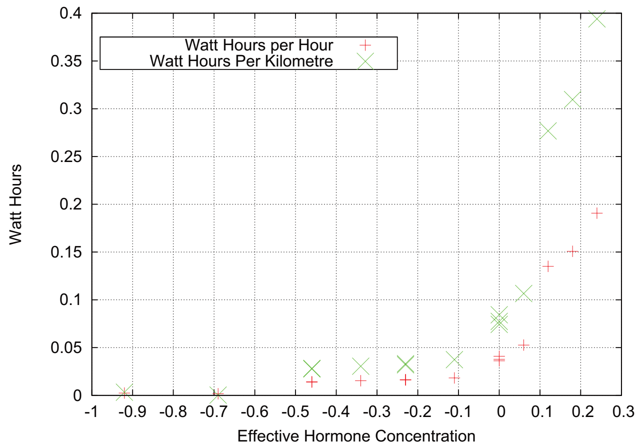

Fig. 3. Diagram showing the correlation between hormone concentration and power consumption in simulation.

TABLE III

SUMMARY RESULTS FROM THE SIMULATOR FIXED HORMONE LEVEL EXPERIMENT

Effective Hormone Conc.	Hormone Sens.	Batt. Level (Watt hours)	Watt Hours / km	Watt Hours / hour	Course Complete?
0	0	5	0.038	0.077	yes
-0.23	0.25	5	0.017	0.033	yes
-0.46	0.5	5	0.014	0.028	yes
-0.69	0.75	5	0.002	0.000	no
-0.92	1	5	0.003	0.003	no
0	0	25	0.041	0.084	yes
-0.11	0.25	25	0.018	0.037	yes
-0.23	0.5	25	0.016	0.032	yes
-0.34	0.75	25	0.015	0.031	yes
-0.46	1	25	0.014	0.028	yes
0	0	55	0.036	0.074	yes
0.06	0.25	55	0.053	0.107	yes
0.12	0.5	55	0.135	0.277	yes
0.18	0.75	55	0.151	0.310	yes
0.24	1.0	55	0.191	0.394	yes

upon the neural network causing greater than normal actuator movements. It is hoped this would lead to more accurate sailing and use what could be seen as excess power to sail better. The intercept value of -1.03 originated in an earlier nonlinear version of this formula and probably could have been approximated to -1.0. When the output is below zero there will be an inhibitory effect upon the neural networks, so as the battery level drops the level of inhibition will increase, hopefully resulting in lower power consumption.

In biological systems, the normal level of a hormone is not a zero value. This leaves two options for the implementation of an artificial system. The gland can constantly secrete hormone under normal circumstances, or the normal situation can be signaled by the absence of hormone. For the purpose of the experiments in this paper the latter is chosen and normal behavior is considered to be when no hormone is secreted. The idea of a hormone being both suppressive and excitory is also present in biology. However, in biological systems a hormone can be suppressive to one group of target cells, while being excitory to another. At present the complexity of our control systems does not warrant a need for this.

Hormone sensitivities of 0, 0.25, 0.5, 0.75, and 1.0 are used, a sensitivity level of zero will act as a control and should cause no modulation of the target neural network. Battery levels of 5, 25, and 55 watt hours are used. By calculating the arising hormone concentration using (10) and multiplying it by the hormone sensitivity we create an effective hormone concentration value, this ultimately determines the level of modulation taking place in the neural network.

A simulation is carried out using a fixed distance course consisting of three waypoints in a 500-m straight line running east/west. A waypoint is placed at each end of the 500 m and one in the middle. The middle waypoint is used to ensure that the robot stuck close to the course. The entire course (1 km from the start point and back to it) is repeated five times in total. The wind is set to blow from the north at a constant speed of 7 m/s.

A summary of the experiments is shown in Table III. The two with the lowest effective hormone concentrations (the highest level of inhibition) both failed to complete the course and are terminated by manual intervention when it is realized that there is no possibility of them completing the course. Fig. 3 shows a graph comparing the power consumption per km and per hour of travel time against the hormone concentration.

These results suggest that there may be a correlation between the concentration of the hormone and amount of energy used. This leads us to generate the following statistical hypothesis for the Spearman's rank correlation (rho):

H_0: Reducing hormone concentration does not affect energy use.

H_1: Reducing hormone concentration reduces energy use.

This forms a one-tail test as we are only testing against a decrease in energy use as the hormone concentration drops. The correlation coefficient is calculated using the R cor.test command[3]; however R cannot calculate significance values for a Spearman's correlation so these are looked up in a significance table in [31]. Note that both power usages per hour and per kilometer are the same in this case because the ranks of the respective results are the same. This results in $P = 0.9910377$ and using the 1% significance level where $n = 15$ and $P > 0.604$ we can accept H_1.

B. Variable Level Battery Hormone

The purpose of this second experiment is to use a varying level hormone, which modulates actuator movement in response to battery levels. This will test the controllers ability to respond to a single varying condition. As in the previous experiment, the hormone will be produced in response to battery levels using (10). The battery level will begin at 55 Wh and each movement of the actuators will reduce the overall battery level. There will be no solar panels or any other power source being simulated to recharge the batteries. As this experiment is expected to take considerably longer than the previous one and due to limitations on computational resources

[3]http://www.gardenersown.co.uk/Education/Lectures/R/correl.htm#correlation

the decision is taken to multiply the power consumption figures by 100. This brings the power consumption for each sail movement to 38.14 J (0.010594 Wh) and each rudder movement to 111.92 J (0.03109 Wh). As computer and sensor power consumption is not being considered, this figure is probably closer to real overall power consumption figure, than those used in the previous experiment.

The course from the previous experiment is extended to 5000 m and the robot set to repeatedly sail the course until the battery is discharged. Increasing the course length made the trials take longer and allows the robot to settle on course for a more realistic period between turns. This allowed assessment of how the hormone sensitivity affected the time taken to discharge the battery. The hypothesis is that the greater the hormone sensitivity the longer the boat will sail: increased modulation will reduce power consumption. As a hormone sensitivity of 1.0 resulted in the boat becoming totally unsailable in the previous experiment only the sensitivities 0.0 (as a control), 0.25, 0.5, and 0.75 are used in this experiment. Each of these is repeated five times to ensure that the results are not a chance occurrence. As with the previous experiment the hormone response rate, which governs the release and decay rates (r in (8)) is set to 0.1.

1) Results: Fig. 4 shows the median battery level over time during these experiments. The stepped effect, which can be seen particularly for sensitivity 0.0, is due to little power being needed between waypoints, but there being high power demands as the boat reaches a waypoint and needs to adjust course and adjust its sails. In the 0.25, 0.5, and 0.75 sensitivity runs the power consumption appears to drop steeply for around the first 100 min and then it begins to slow. This is soon after the point where the battery crosses the 44.8 Wh threshold and the hormone switches from being excitory to inhibitory.

It is noted that sometimes the sail would oscillate between two positions when on a boundary. This is most common while the hormone is still excitory. Added to this is that when reaching a waypoint and turning the boat 180° requires both the sail and rudder to move dramatically, which (especially when the hormone is excitory or only slightly suppressive) uses considerable amounts of energy. This behavior reduces as the battery level drops and the level of hormonal suppression on the actuators increases. This does bring into question whether anything useful is being gained by having this hormone operate in an excitory manner and whether simply having it operate as a suppressive hormone would be sufficient, even if it only became suppressive when the battery level dropped below a threshold amount, rather than becoming to suppressive as soon as the battery dropped below full.

There is a clear correlation between sailing time and hormone sensitivity. The median time that the boat is able to sail for increases from 568.95 min for a sensitivity of zero (no modulation) to 2552.28 min for a sensitivity of 0.25, 4653.73 min for a sensitivity of 0.5, and 7642.9 min for a sensitivity of 0.75. A box and whisker plot is shown in Fig. 5. This shows that there is quite a small spread and few outliers to this data. To ensure these changes are not simply a result of the boat slowing down and covering less distance the analysis is repeated using the distance covered. These values are shown

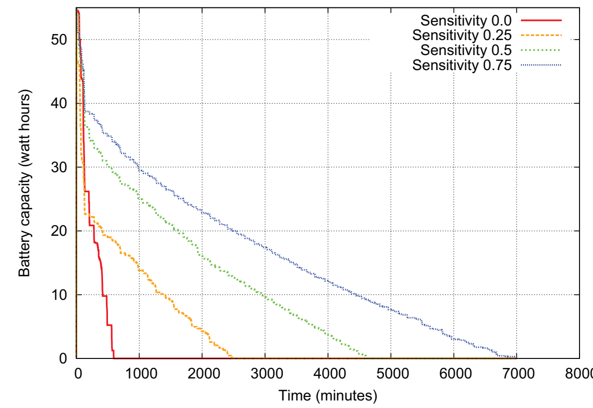

Fig. 4. Graph of the median battery level over time, during the simulation runs with hormone sensitivities of 0.0, 0.25, 0.5, and 0.75.

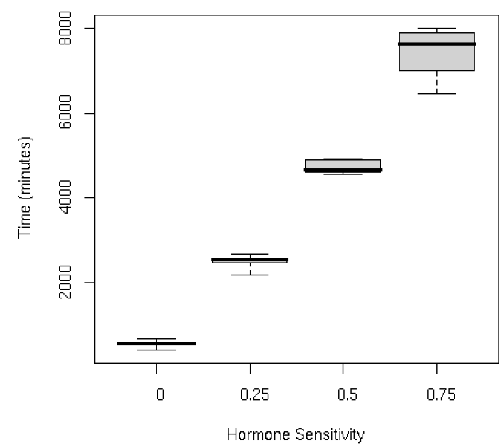

Fig. 5. Box and whisker plot of the simulator's battery discharge time and hormone sensitivity during the variable battery hormone experiment.

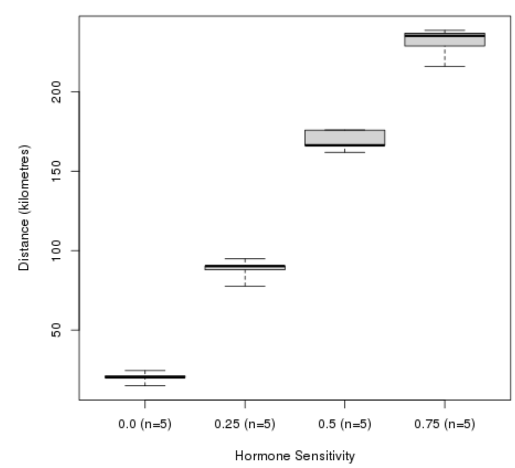

Fig. 6. Box and whisker plot of the simulator's distance covered and hormone sensitivity during the variable battery hormone experiment.

as a box and whisker plot in Fig. 6. These results mirrored the same trend, showing median distances of 20.2 km for a sensitivity of zero (no modulation), 90.3 km for a sensitivity of 0.25, 166.3 km for a sensitivity of 0.5, and 235.2 km for a sensitivity of 0.75.

A Kruskal–Wallis test (nonparametric analysis of variance) is performed to test if the differences caused by varying hormone sensitivities is statistically significant. As this test operates on ranked data the results for both distance covered and time taken are identical as the ranks of the data are the same. The results are calculated in R[4] using the kruskal.test command. We test the following hypotheses:

H_0 : Varying hormone concentration does not affect the time or distance that a robot can sail on a single battery charge.

H_1 : Varying hormone concentration does affect the time or distance that a robot can sail on a single battery charge.

$H = 17.8571,\ df = 3,\ p = 0.0004707.$

Given that $p = 0.0004707$ (0.4707%) we can accept H_1 at the 1% significance level. There is a statistically significant change in both time and distance that can be achieved on a single battery charge.

C. Solar Power Simulations

Further experiments are undertaken to investigate the effect of the endocrine control system when the robot's battery can be recharged from a photovoltaic solar panel. This tested the ability of the controller to maintain a homeostatic state of keeping the battery charged when the robot has only limited power to achieve this. It also demonstrated the ability of the controller to sychronize its behavior with an oscillating external environment. Photovoltaic solar panels have the potential to give perpetual operation to the robot however, as discussed in Section III-C.1 the simulated solar panels only generate a maximum of 4.75 W. The previous experiment (in Section IV-A) showed that simulated actuator power consumption will be between 0.666 and 9.333 Wh/day; however evidence in Section III-C.1 and in [28] suggests that using the figure multiplied by 100 as in the previous experiment may be closer to the reality of a real small scale sailing robot. As this will be in excess of the solar power budget some portion of the day will have to be spent in a highly suppressed state (not sailing effectively).

Two approaches are taken to control the solar powered system here: the first is to simply have the control system feedback through the battery levels. This is likely to lag behind the solar output by a few hours and thus power consuming behavior may continue after the sun has gone down. The second is to have an additional hormone track the level of the sun or the near future level of the sun, so if we enter a situation where battery is low but we have several hours of sunlight to come then it might be acceptable to not suppress power consumption. Conversely, if we have significant amounts of battery left but little sunlight in the near future then we should adopt a more conservative strategy. This approach could be extended to cover seasonal variations as well as daily ones, which might be of more use for robots with larger batteries that can survive several days without recharging. However, smaller robots (or our simulated robot) need to operate on daily cycles since their batteries cannot last more than a few days.

[4]http://www.r-project.org

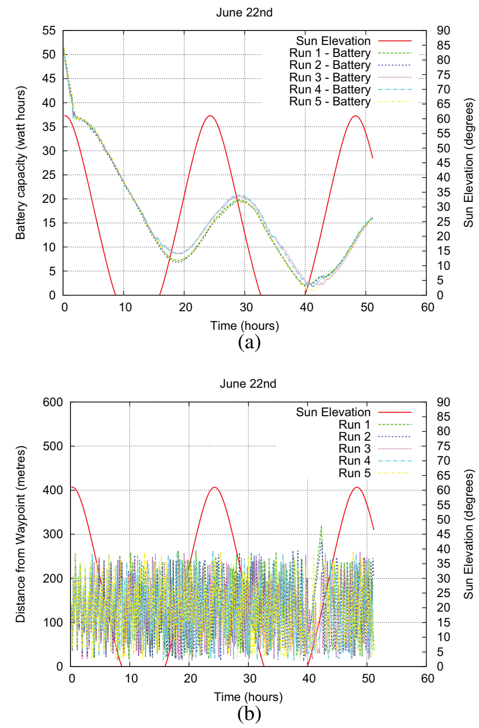

Fig. 7. Graph showing the results of the solar power simulations with only a battery hormone running in June. (a) Battery levels and sun's angle of elevation over the duration of the experiment. (b) Boat's distance from the waypoint during the experiment alongside the sun's angle of elevation.

As there is the potential for some of these experiments to result in perpetual operation a termination mechanism is required. A course of 400 waypoints each 250 m apart (100 km total course length) is setup. Simulations are terminated when the battery level reaches zero or once all waypoints are visited. As with previous experiments the waypoints are setup so the boat sails back and forth on a beam reach, with the wind perpendicular to the course.

No formal hypotheses or statistical tests are made for these experiments, as the selection of hypotheses would have been arbitrary and would not usefully add to the evidence for the changes in performance seen in the plots.

1) Solar Power Simulations With Only Battery Hormone: For the first of the solar experiments, the hormone configuration used is the same as in the previous experiment (in Section IV-B). Thus, the only feedback to the control system of the sunlight levels is through the battery level hormone. The battery hormone sensitivity is set to 0.75. This value is shown in the previous experiment to apply the maximum level of modulation without causing problems to the boat's ability to sail. Five runs of each experiment are carried out to help ensure that any conclusions are not due to a chance event. The experiment is repeated on the simulated dates of June 22, September 22, and December 22 to approximately cover the summer solstice, autumnal equinox, and winter solstice, respectively. Each run began at solar noon.

Figs. 7(a), 8(a), and 9(a) show graphs of the sun elevation and the battery level for these simulations. In the June simulation, the course is completed in all cases in around 50 h. Given the level of sunlight in June this would allow this

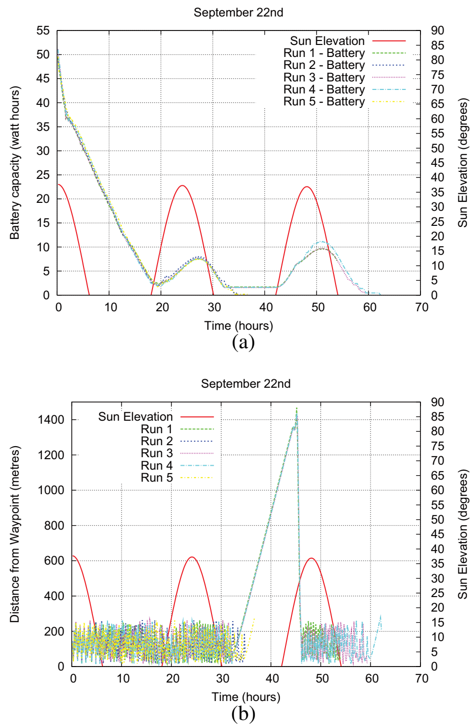

Fig. 8. Graph showing the results of the solar power simulations with only a battery hormone running in September. (a) Battery levels and sun's angle of elevation over the duration of the experiment. (b) Boat's distance from the waypoint during the experiment alongside the sun's angle of elevation.

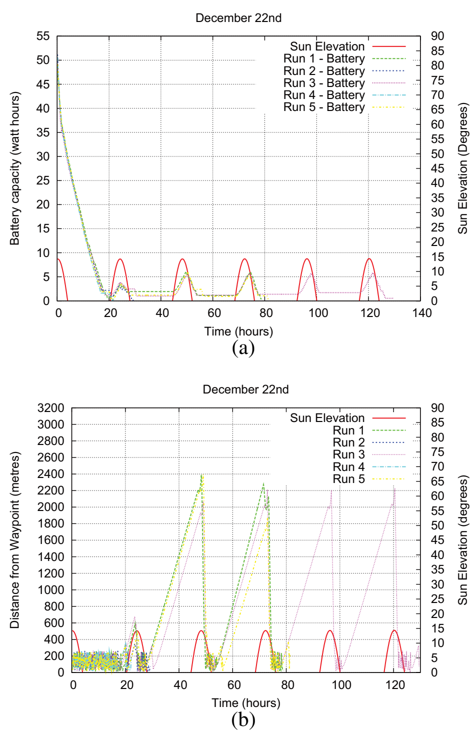

Fig. 9. Graph showing the results of the solar power simulations with only a battery hormone running in December. (a) Battery levels and sun's angle of elevation over the duration of the experiment. (b) Boat's distance from the waypoint during the experiment alongside the sun's angle of elevation.

course to be repeated indefinitely. In September and December, the course is not completed and a flat battery is the cause of the simulation terminating. The September graph shows that two of the experiments ran out of battery after only approximately 35 h. The other three September experiments have suppressed their control systems sufficiently to consume no power all night, and only begin to consume any power again the next morning. This same behavior is seen to an even greater degree in the December experiments, where two simulations end within 30 h, another two manage to last 80 h by performing no activity at night, and another manages to last nearly 130 h. While this could be considered desirable, it should be noted that the reason they are consuming no power during the night is because the battery is so low that the solar hormone has totally suppressed any actuator movement and therefore, the boat is just continuing to sail whatever course it was set previously.

This can be confirmed in Figs. 7(b), 8(b), and 9(b), which show the distance of the robot from its waypoint over time. As the distance between waypoints is only 250 m, under normal circumstances this distance should never be significantly more than 250 m. In cases when it does dramatically exceed this, it is an indication that the control system has not succeeded in keeping the robot sailing toward the waypoint and has instead let it overshoot the waypoint and continue sailing away.

In the June simulation the robot is never more than approximately 300 m from the waypoint and this value is constantly fluctuating. In the September simulation some of the experiment runs travel as far as 1500 m from the waypoint. In the December simulation the robot spends large amounts of time overshooting the waypoint getting over 2000 m from the waypoint on several occasions. These overshoots are due to it being in a sailing state when the control system stops performing any action due to a low battery. This behavior is not ideal and could be improved by lowering power consumption during the day so that battery levels are higher at night.

2) Solar Power Simulations With Sunlight Level and Battery Hormone:

$$h = 0 - (x/90). \tag{11}$$

This experiment kept the original battery response hormone and introduced a second hormone, which is produced in inverse proportion to the elevation of the sun. The hormone is produced according to formula (11) where h is the hormone quantity produced (ranging from 0 to -1.0) and x is the elevation angle of the sun between 0 and 90. This hormone is only inhibitory, and will produce its maximum level of inhibition when the sun is below the horizon and no inhibition when the sun is directly overhead. The previous experiment is rerun with this extra hormone. The sensitivity to the new hormone is also set to 0.75. The release/decay rate is set to 0.1, as is used with the battery hormone in this and the nonsolar experiment in Section IV-B.

Figs. 10(a), 11(a), and 12(a) show the battery and sunlight levels for these experiments. In all cases the robot is now able to complete the course, with the June simulations taking around 75 h, the September simulations between 80 and 120 h and the December simulations over 350 h. However, in all cases this is achieved at least in part by having the robot make no movement at all during the night. Figs. 10(b), 11(b),

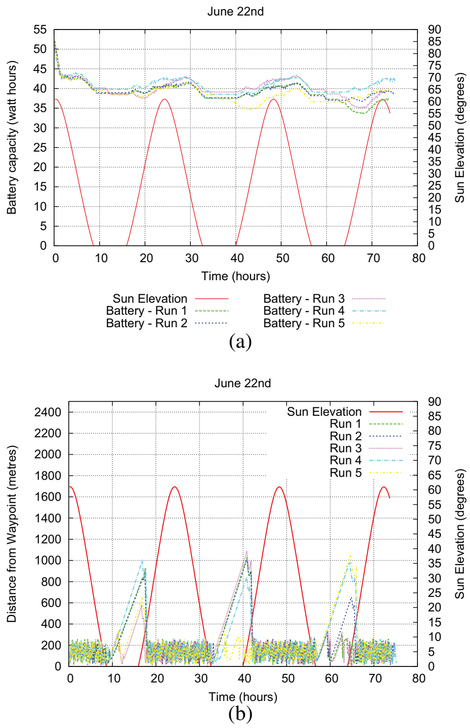

Fig. 10. Graph showing the results of the solar power simulations with both a battery and solar hormone running in June. (a) Battery levels and sun's angle of elevation over the duration of the experiment. (b) Boat's distance from the waypoint during the experiment alongside the sun's angle of elevation.

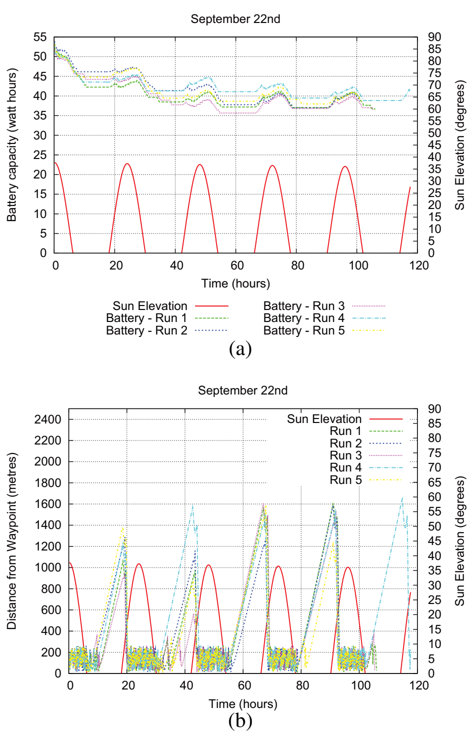

Fig. 11. Graph showing the results of the solar power simulations with both a battery and solar hormone running in September. (a) Battery levels and sun's angle of elevation over the duration of the experiment. (b) Boat's distance from the waypoint during the experiment alongside the sun's angle of elevation.

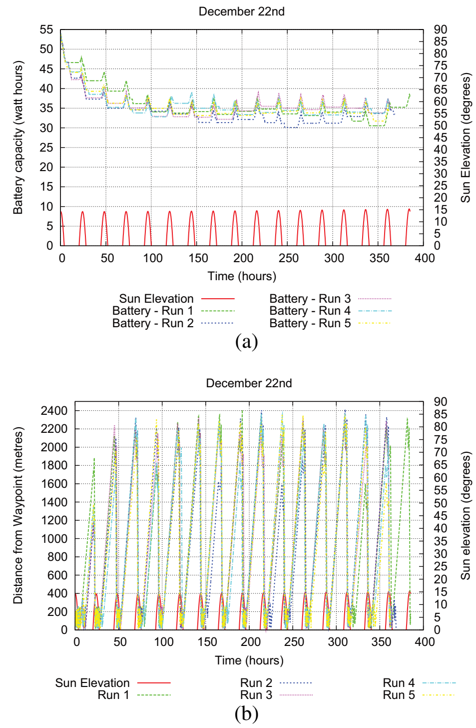

Fig. 12. Graph showing the results of the solar power simulations with both a battery and solar hormone running in December. (a) Battery levels and sun's angle of elevation over the duration of the experiment. (b) Boat's distance from the waypoint during the experiment alongside the sun's angle of elevation.

and 12(b) show the distance from the waypoint. Compared with Figs. 7(b), 8(b), and 9(b), we can see that distances from the waypoint have increased. In all cases the amount of time spent more than 250 m away from the waypoint has increased substantially, due to the amount of time the control system has spent being suppressed, to the point where the boat cannot sail. However, it is only by doing this that the robot is able to complete the course.

Given the power budget constraints it would be impossible to complete the course without completely suppressing the control system during September or December. However, it might be possible during June, suggesting that the hormone sensitivity level for the sun elevation hormone is too high.

These results show an example of how two hormones can help to reinforce a given behavior. They also show an example of a sustainable homeostatic system, which is able to maintain battery levels perpetually, although this is essentially achieved through a deep sleep, which totally suppresses the control system for much of the day. Despite the obvious dangers of doing this, the boat never strays further than 2.5 km from its waypoint. In a number of off-shore scenarios, if the boat could remain within 2.5 km of its intended course, this might be sufficient for safe operation.

V. Robot Experiments and Results

A. *Fixed Hormone*

The experiment from Section IV-A is repeated on the robot. As with the simulator, the boats are sailed on a beam reach course, although this is limited to 150 m in length because of the size of the lake being used. Because of the time it took to perform each run, the experiment is run over the course of

TABLE IV
COMPARISON OF NUMBER OF HOURS AND KILOMETERS TRAVELLED FOR EACH WATT HOUR OF ENERGY USED DURING THE ROBOT FIXED HORMONE EXPERIMENT

Hormone Conc.	Hormone Sens.	Batt. Level (Watt hours)	Watt Hours / km	Watt Hours / hour	Course Complete?
0	0	5	0.628	0.491	Yes
-0.23	0.25	5	0.814	1.072	Yes
-0.46	0.5	5	0.535	0.666	No
-0.69	0.75	5	0.184	0.170	No
0	0	25	1.281	1.588	Yes
-0.11	0.25	25	1.064	1.261	Yes
-0.23	0.5	25	0.909	1.145	Yes
-0.34	0.75	25	0.793	0.948	No
0	0	55	2.233	3.095	Yes
0.06	0.25	55	0.956	1.204	Yes
0.12	0.5	55	1.471	1.064	Yes
0.18	0.75	55	1.018	1.340	No

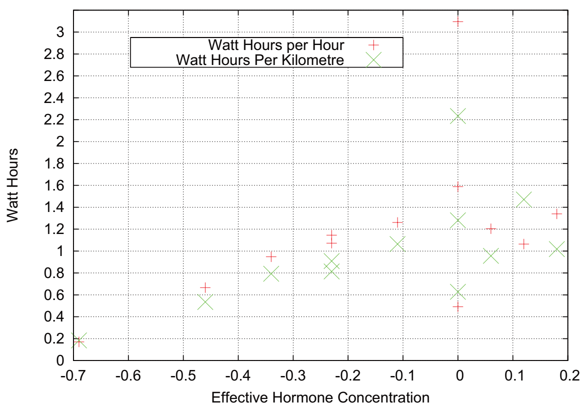

Fig. 13. Graph showing the relationship between power consumption and effective hormone concentration. Power consumption is normalized to watt hours per kilometer (green Xs) and watt hours per hour (red + s).

several days. Each run repeats the course two or three times, as the exact waypoints varied to accommodate changing wind directions (from one day to the next) to ensure a beam reach course is possible.

The results of this experiment are presented in Table IV. Fig. 13 shows the relationship between the hormone concentration and power consumption both per kilometer and per hour of travel. From this graph, a correlation between the power consumption and hormone concentration can be seen, as there is the case in the simulation experiment in Section IV-A. This leads us to generate the following statistical hypothesis for the Spearman's rank correlation (rho):

H_0: Reducing hormone concentration does not affect energy use.

H_1: Reducing hormone concentration reduces energy use.

Using a one-tail test, this shows that for the energy use per km, $P = 0.6455$ and using the 1% significance level where $n = 12$ and the threshold being $P > 0.678$ we cannot accept H_1, however at the 5% significance level where P must exceed 0.503 we can accept H_1. The same applies to the energy use per hour where $P = 0.5075$.

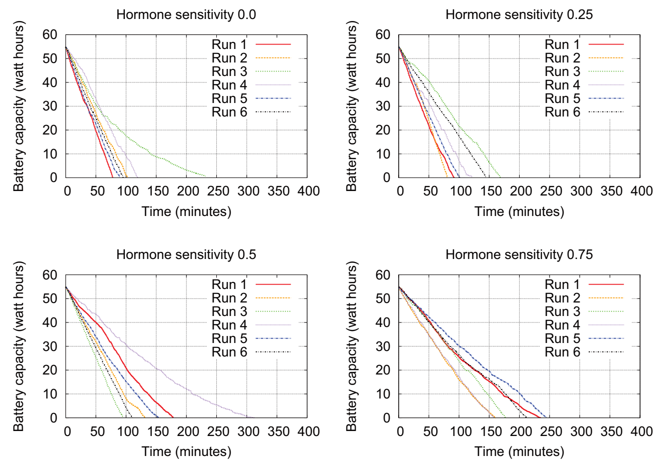

Fig. 14. Graphs showing the battery discharge over time during the variable hormone robot experiments, with hormone sensitivity levels of 0.0, 0.25, 0.5, and 0.75.

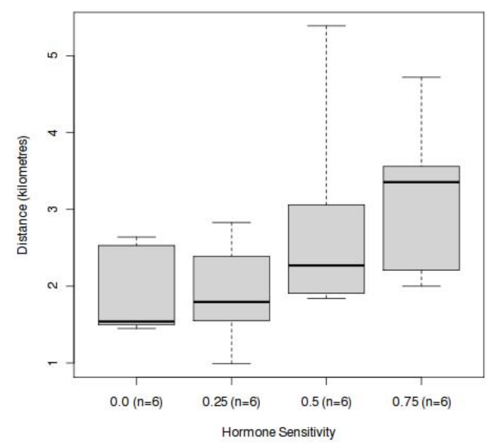

Fig. 15. Box and whisker plot of the robot's battery discharge time and hormone sensitivity during the variable hormone experiment.

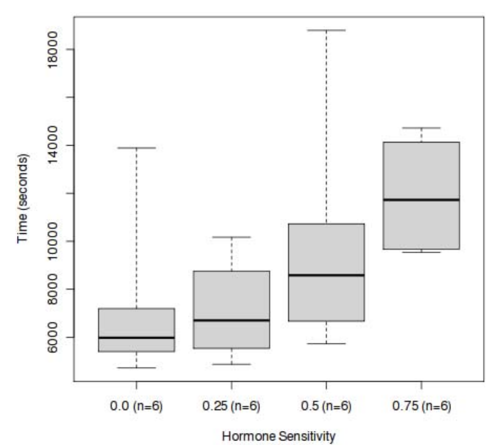

Fig. 16. Box and whisker plot of the distance covered by the robot in one battery discharge and hormone sensitivity during the variable hormone experiment.

B. Variable Hormone

We repeated the variable hormone experiments from Section IV-B.1 upon the robots. For each hormone sensitivity level the experiment is repeated six times, three times on each robot, as a result this experiment took several months to complete. As the boats had no hardware to measure the actual battery state of charge, the same simulated state of charge system described in Section III-C.1 is used. This had the added advantage that the robot did not actually end up with a flat battery while in the middle of the lake.

The battery discharge over time is shown in Fig. 14, Fig. 15 shows a box and whisker plot of the amount of time the robot is able to sail for, and Fig. 16 shows the same for the amount of time the robot is able to sail.

To test for a statistically significant difference a Kruskal–Wallis test (nonparametric analysis of variance) is performed. This led to the statistical hypothesis that:

> H_0 : Varying hormone concentration does not affect the amount of time that it is possible to sail on a single battery charge. H_1 : Varying hormone concentration does affect the amount of time that it is possible to sail on a single battery charge.

Kruskal–Wallis $H = 9.0067$, $df = 3$, $p = 0.0292$.
Given the p value of 0.0292 (2.92%) we cannot accept the alternative hypothesis at the 1% significance level although we can accept it at the 5% level.

VI. Discussion

The initial results from the fixed hormone experiments demonstrate that hormonal modulation can have a dramatic effect on the power consumption of a neural network controlled sailing robot, both in simulation and a real robot. There is a correlation between the level of hormonal modulation and power consumption both per kilometer travelled and for each hour of travel. Although the correlation of the robot experiments is not as strong as the simulator, it is still statistically significant. The discrepancy between the simulator and real robot is likely to be due to the difference between the simplistic physics model of the simulator and the much more complex and noisy reality facing the robot. In both the simulator and robot, increasing the hormone concentration eventually caused experiments to fail with the boat unable to navigate around the course. This may suggest that for the task at hand the control system is far too active and that up to a point this activity can be reduced when operating in light winds and flat seas offered by these scenarios. However, in real life the control system needs to cope with a wide variety of conditions and some level of tolerance to harsher conditions is required [28]. This experiment shows that when conditions are calm this margin of error can be taken away without impeding performance. This therefore goes some way to confirming that this can also be used as a method for controlling power consumption. We may, however, wish to create some kind of counteracting hormone that depends upon sea state.

The simulated variable hormone experiment saw the median battery life time range from 565 min in the control (hormone sensitivity of 0.0) to 7401 min with a sensitivity of 0.75. Although less dramatic, the robot experiment sees the median time rise from 119.9 (hormone sensitivity 0.0) to 198.6 min (hormone sensitivity 0.75). The simulator battery discharge curves in Fig. 4 show an inverse exponential shape, which is expected from the experiment, while the robot experiments (Fig. 14) are closer to a linear shape. This suggested that other factors not present in the simulation have significantly influenced the robot's battery discharge. These are likely to relate the action of the waves and the noise of operating in a real world environment. However, hormonal modulation still had a significant effect upon the overall power consumption.

VII. Conclusion

The results in this paper showed that applying endocrine inspired modulation to a neural network offered a powerful mechanism for controlling power consumption in robotic systems. This method created an artificial homeostasis, in which a stable internal state can be maintained with respect to battery life, by trading off power consumption against the performance of the robot. An artificial neuroendocrine system offered a mechanism to modify the behavior of a neural network over varying timescales and overcame the problem of dealing with time series data in a neural network. Within the context of power management, many traditional systems have relied on rule based methods with a Boolean power saving mode. A hormonal system offered a (near) continuous set of states ranging from no modulation to complete suppression, allowing for gradual switching between behaviors. This allowed for a tradeoff between multiple goals or for multiple behaviors to reinforce each other. This can be viewed as an action selection mechanism and compared with winner takes all and rule-based approaches where only a single behavior was active at any time and behaviors were either ON or OFF.

While the results presented in this paper provided a promising start, further work is needed to validate them in more realistic and longer term scenarios. Work is currently underway to repeat these experiments using a 3.65 m long sailing robot [32], capable of remaining at sea for extended periods. This will attempt to scale the system to a scenario that is far more variable than a simulator or an inland lake.

Future work will also include an expansion to include additional hormones. Potential hormones might represent sea state, distance to waypoint or the proximity to obstacles. Also of interest is the concept of creating an artificial hormone cascade, the process in which one hormone triggers the production of one or more other hormones. In biological systems this acts to amplify small quantity of an initial messenger into sufficient quantities to activate large scale global responses. The cascade also has the potential to create a delay between the initial hormone release, the release of hormones further on in the process, and feedback to stop the production of the initial hormone. An artificial cascade could therefore be used to ensure that a new behavior is selected for a minimum amount of time and prevent rapid oscillation between behaviors.

A key limitation of the neuroendocrine architecture presented in this paper was the lack of online learning abilities, the system was instead reliant on prelearnt rules. This could lead to situations where the system will take an incorrect action, recover from it, and then repeat the same incorrect action later. Some form of constant online learning mechanism could address this. Potential strategies include applying a

Hebbian learning algorithm [33], a clonal selection algorithm [34], a success/failure map [35], or kernel-based methods [36].

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Colin Sauzé received the Ph.D. degree from Aberystwyth University, Aberystwyth, U.K., in 2011, in endocrine inspired power management of sailing robots.

He is a Post-Doctoral Research Associate with the Department of Computer Science, Aberystwyth University. His current research interests include mobile robotics, ocean going robots, and biologically inspired systems.

Mark Neal is a Senior Lecturer of computer science with Aberystwyth University, Aberystwyth, U.K., where he leads the Intelligent Robotics Research Group. His Ph.D. and the majority of his research work have been in the use of bio-inspired algorithms for computation and control systems. His current research interests include the development of mobile robots and ocean-going sailing and the application of bio-inspired algorithms to this domain.