Master thesis on Cognitive Systems and Interactive Media

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OVERCOMING ALLOSTATIC CHALLENGES THROUGH PREDICTIVE ROBOT REGULATORY BEHAVIOR

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Abstract:

Internal processes such as homeostasis and allostasis operate to keep the internal environment within desired conditions to sustain fitness by satisfying rising needs such as thirst or hunger. However, when two or more needs are to be satisfied, the organism faces a conflict and based on diverse factors, from interoceptive sensations to external stimuli from the environment, one of the needs is prioritized and satiated over another. Allostasis, as a predictive mechanism, is at the core of effective regulation and conflict resolution. In this work, we simulate competing emerging needs such as thirst and internal temperature by adding a feedforward module (Allostasis), responsible for the predictive behavior of a simulated agent over an already existing model of reactive homeostasis, in which the agent is placed within an environment of constantly changing temperatures. Incorporating the anticipatory layer happens at two conditions, single and multiple drive prediction, and it is hypothesized that the agent under the predictive conditions will have less homeostatic error over time compared to the reactive one. The results show a significant reduction of homeostatic error on both conditions upon the addition of the feedforward controller, supporting and contributing to the literature on allostatic anticipation and effective regulatory control. Moreover, methodological recommendations for further research are given based on the limitations found in the development of this study.

Keywords: Behavioral Regulation, Allostasis, Homeostasis, Conflict resolution, Biomimetic Robotics.

1. Introduction

1.1 Problem Statement

Life depends on maintaining interacting metabolic reactions. Internal processes happening from unicellular organisms to complex animals and plants operate to keep the internal environment within desired conditions to sustain fitness. Such regulatory processes were first described under the word homeostasis by Claude Bernard, a term created to refer to the control at the level of cells and organs [1].

Under the assumption that reduced entropy is the driving force of evolution, it has been suggested that homeostatic control as a process of regulation has been sustained and perpetuated as a trait in living organisms because of its power to maintain the status quo of the internal environment, and therefore its faculty to reduce entropy. From a biological perspective, homeostasis evolved to protect organisms from harmful variations in physiological factors and to promote adaptation [2]. Regulatory processes are therefore extremely relevant for living organisms and understanding the ways in which they operate is still a work in progress.

After the term homeostasis was coined, other terms have emerged to give more accurate descriptions of regulation in accordance with recent research [9]. Nowadays, terms such as allostasis and interoception are also key in the understanding of physiological and psychological regulation. In the present work, concepts related to regulation are used under a hierarchical model in which interoception is located at its base and understood as the sensations related to the body's states [3]. In case interoceptive sensations are signaling abnormal conditions, the process of regulation will lead to the middle layer, homeostasis, which excerpts control over cells and organs to reduce abnormality. Finally, as an encompassing layer, there is allostasis, which refers to the achievement of regulation by orchestrating at a holistic level and in a predictive manner [1]. The present study ventures into the development of a simulation that recreates the anticipatory feature of allostasis in a synthetic agent presented with thirst and low temperature as competing needs, to compare its performance with a non-anticipatory homeostatic model.

The development of such simulation adds to the literature of motivational conflict resolution and addresses the lack of computational models of predictive allostasis. Some of the previous computational work about allostasis and its predictive component has been done by Alexander

Tschantz et al [4] who have developed a series of simulations of interoception, homeostasis and allostasis under the framework of active inference. Additionally, Jimenez et al [23] have contributed to the development of computational models via attractor dynamics that simulate the resolution of motivational conflicts when two emergent needs arise. However, the development of models using allostasis as both conflict resolution and predictive control are still limited in the literature. The present work uses control theory to model allostatic prediction, which has been described theoretically, although not yet implemented in a simulated environment, making it an opportunity to explore the theoretical correspondence between control theory and anticipatory regulation by computational means.

1.2 State of the art

The principle underlying the regulation of internal needs was first described in 1929 by Walter Cannon as homeostasis inspired by Claude Bernard's definition of the "internal milieu"- a constancy in the internal environment of certain organisms regardless of external disturbances [7]. Cannon decided to coin the term to define how body systems monitor and preserve a set of vital parameters from deviations through physiological or behavioral means; thermoregulation is an example of homeostasis. In a quest to maintain a range of temperatures, the body will perform a series of physiological and/or behavioral responses depending on the perceived disruption, when the inner temperature exceeds the desired range, (e.g., a hot day) people will normally sweat, whereas when the temperature is below the range (e.g., a cold day), vasoconstriction will happen [10]. Initially, homeostasis was mainly related to physiological systems such as the cardiovascular or respiratory one, but it has been expanded to the use of social or psychological needs as well [11]. Cannon's relevant addition to the field of physiology by adding the term of homeostasis was to include behavior and emotion of the organism in the scheme of control of the internal environment [10] under this paradigm, balance in the internal milieu can be achieved not only through physiological responses, but through behavior as well [14]. How homeostatic imbalance could motivate behavior was further discussed by Hull (1943), who developed the drive-reduction theory in which unbalanced states in homeostasis induce a drive state, that is, a state of discomfort that pushes the animal to perform regulatory behaviors towards relief, achieving "drive reduction" and with it, homeostatic balance. Actions such as wearing clothes or remaining in a shelter when faced with extremely cold temperatures illustrate how drive reduction is reached through behavior [10]. Other examples of behavioral responses to homeostatic imbalances can be seen in rats or reptiles.

When hungry, rats tend to exhibit a magnified foraging behavior compared to those fed [11] in this scenario the disturbance to homeostasis balance related to hunger is compensated as a consequence of behavior. Similarly, when faced with deviations of normal thermal ranges, reptiles rely on behavioral responses to restore normality; actions such as shuttling between sun and shade or change in body posture, are performed to reach normal ranges [14]. Since homeostasis can be understood as a predominantly reactive approach to regulation, models that operationalize homeostatic control have been developed by using terminology from control theory [11].

Following the analogy of control theory, homeostasis has been equated to a feedback controller. Under this perspective, a homeostatic process can be understood as a scheme of error detection and correction. [6] When a variable, for instance thirst, is found to diverge from the desirable value, an effector mechanism is activated to restore values under the set rates, generating a physiological or/and behavioral reaction[13]. To make a clearer depiction of how a homeostatic controller works and to specify its different states, Lallée, S et al [14], Volutsi, V et al [15] & Guerrero-Rosado, O & Verschure, P [16] have proposed to classify the motivational drives into three different states: (1) under homeostasis, (2) homeostasis, and (3) over homeostasis. Figure 1 shows a homeostatic system with maximum and minimum values. The system can be labeled as a balanced or in a homeostasis state, while the actual value (aV) stays within the desired value range (dV). Once (aV) moves below or above the maximum limit, the organism will find itself at an under, or over homeostasis state respectively [14] [15].

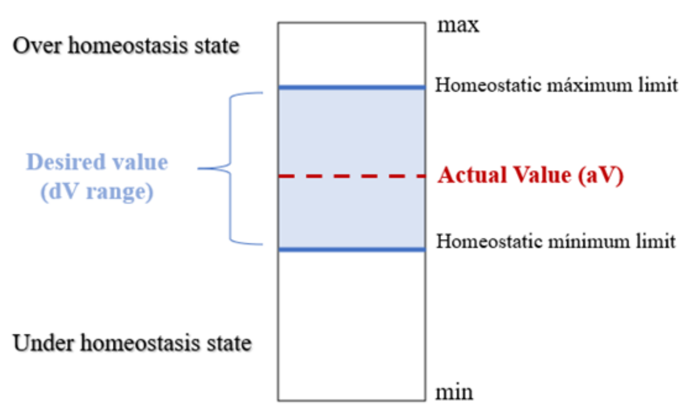

***Figure 1: Homeostatic control**. Keeps the actual value (aV) of the controlled parameter within the desired value (dV) range. The dV range is determined by the values of homeostatic limits. Reproduced from [14]–[16].*

Physical responses to homeostatic imbalance happen unconsciously and rely on autonomic processes [9] unless behavior is needed to perform regulation. The way in which such responses are triggered happens due to the organism's interoceptive capabilities. Just like homeostasis, interoception was a term originally used only in the scope of physiology to describe the nerve receptors that reacted to the stimuli originated within the body [10] but with time, the term started to be used in a broader sense. Interoception is now understood under a psychobiological framework, in which the behavior and psychology of the organism are also included within the understanding of the term. In this respect, the concept expands, and it is described as "the sense of the physiological condition of the entire body" [3] In other words, interoception allows the organism to sense the physiological state of its body; feelings like hunger, thirst or pain are examples of it.

Although the term homeostasis has been used to describe the regulatory process of an interoceptive organism's internal environment, the concept has encountered some limitations to comprehensively explain the nature of responses to homeostatic imbalance [9]. Sterling [17] clearly defined some of the limitations of understanding the regulatory process only under the scope of homeostasis. The following are the main limitations described: (1) generating responses to imbalances by solely using error correction is inefficient. Reactive behaviors are a starting point to interact with the environment when there is no previous experience. Nevertheless, once some experience has been gained, regulation becomes anticipatory, allowing the organism to prepare itself and compensate for predictive errors before they arise, instead of responding after imbalance affects the system. (2) regulation does not happen under single organ activation, since it would require extensive metabolic resources. An efficient model of regulation requires organs to exchange resources and grant short-term goals to each other in an organized fashion. In an attempt to generate a concept that could overcome the limitations previously defined, a new term was introduced. Allostasis was first defined by Sterling and Eyer (1988) as the way in which the organism varies the parameters of its internal milieu and matches them appropriately to environmental demands [19]. The previous definition brought along some relevant implications in the understanding of regulatory control. First, the idea that control is not merely responsive, but also anticipatory. Second, the way in which control is exerted happens through an orchestration of the body's internal markers, rather than a single organ activation, and third, it locates the orchestration of regulation in the brain [7] [19].

Conceptually, allostasis could be understood as a layer over homeostasis in the sense that it prioritizes and orchestrates responses to competing imbalance in homeostatic values of regulatory systems dysregulations in homeostatic markers of internal drives. Aside from orchestration, allostasis as a process responds predictively to assure a balanced internal environment when dysregulations are likely to take place [16]. Just like homeostasis has been referred to as a feedback control system under control theory, allostasis could be equipped to a fine network of feedforward and feedback mechanisms, generating a flexible and coordinated way to achieve physiological control. The predictive nature of the feedforward module added to the feedback one allows the internal milieu of the organism to predict disturbances in certain parameters and prepare the system to compensate more effectively [18] (e.g., increasing blood pressure before standing up from a chair, rather than correcting the drop in tension induced by the postural change after standing.) [6]

A clear representation of how homeostasis is achieved through allostatic orchestration can be found on figure 2. In the picture, two competing drives -hunger and thirst- are depicted, each within a homeostatic controller. Ranges of desired values (dV) are set in color while the dashed line illustrates the actual value (aV) of each drive. Two behaviors are representative of the response to under-homeostasis state for each drive, foraging when hungry and consuming water when thirsty. The allostatic controller encompasses both homeostatic controllers as it can be seen in the graph, with the purpose of monitoring and assessing both the intensity and the priority of each to respond accordingly [4][11].

Figure 2 depicts a hypothetical situation where a mouse is faced with two competing drives: hunger and thirst. The ranges of the desired values of homeostatic subsystems differ. In this example, hunger results as a more intense drive due to having a higher difference value (dV-aV) when compared to the difference in thirst.

Being hungry is a more intense drive than thirst in the scenario of the graph and will generate the mouse to forage before consuming water. Normally, responses will be measured according to the intensity of the drive, here hunger is expected to override thirst. Nevertheless, when both tendencies are equally urgent, the organism will respond based on the priority principle, since responses to bring balance are done hierarchically, one after the other.

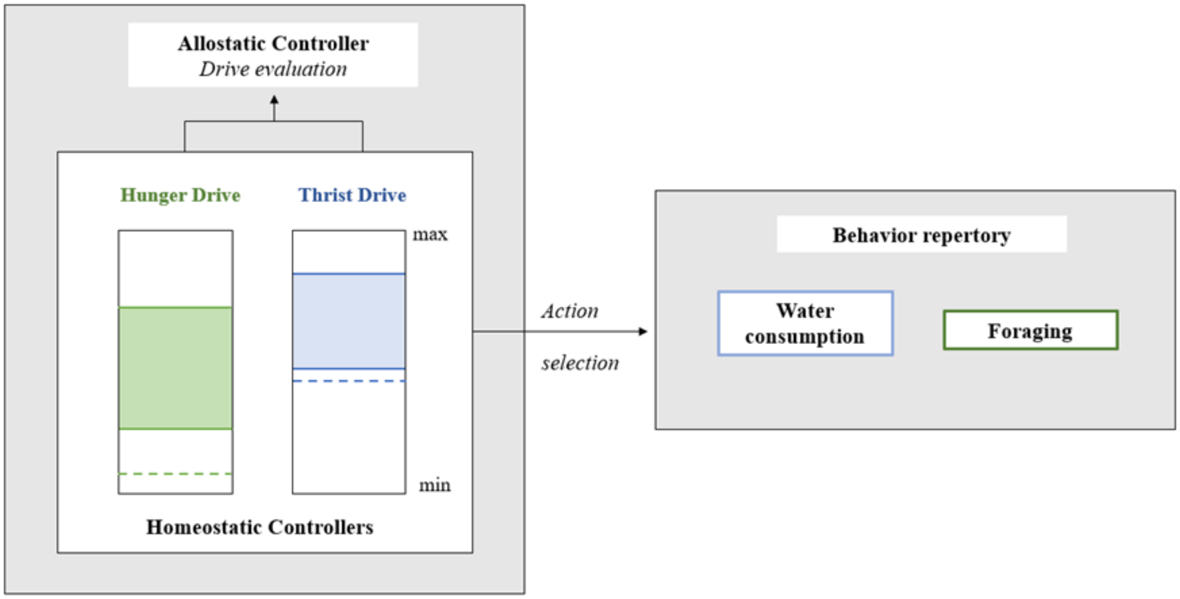

Figure 2: *Diagram of behavior selection. Internal drives are evaluated by means of intensity and priority. In this example, hunger is prioritized over thirst and therefore foraging is chosen. Reproduced from [16][18].*

It is known that response behavior to an abnormal homeostatic state is done separately and sequentially [19]. Therefore, when faced with competing drives –hunger, thirst or any other–, responses will occur as a cascade. In the case of the rodents from the study about competing drives by Burnett et al [11], hunger overrode thirst to promote foraging behavior when animals were deprived of both food and water. The previously described experiment showed complex contestation between water and caloric deprivation, furthermore, it stated as empirical support for the existence of orchestrated, hierarchical, and sequential solutions when competing emerging needs arise. Other studies on competing drives have shown similar results [19], supporting the premise that a specific response to homeostatic imbalance is chosen depending on its relative intensity. The experimental study by LeGraize et al [19] was made with rodents that were induced into a painful state while also being deprived of food. The results showed how the responses to both drives change in respect to their intensity. In early trials with formalin, injected animals that were also hungry tended to address the pain in their paw, either by licking it or elevating it, and did not engage in eating as much as those without the injection. Nevertheless, during the repetition of the trial -phase 2– animals would show less mean pain score. In other words, they did not spend as much time as the first trial in addressing their pain, resulting in higher eating behavior. Lower pain response in phase two was attributed to the decrease in intensity of the formalin injection[21]. Previous examples highlight the existence of competition among drives and how their reduction is done both hierarchically and consecutively.

Empirical examples like those described above have inspired to reproduce allostatic orchestration in synthetic agents under a biomimetic approach; some attempts have been done by [16], [17], [22]. In both experiments, the robot is assigned a set of emotional drives, such as physical interaction, social interaction, spoken interaction and energy, drives which, orchestrated by an allostatic controller can generate certain behaviors when being under or over homeostasis states. That is to say, for example, that once the robot's value for physical interaction is under the desired value, it will respond by shaking the hand of the human to reduce the difference between the actual value and desired value for that specific drive. The authors describe how using allostatic control ensures that the robot's actions will not collide and promotes adaptive biological behavior in an artificial agent [16], [17].

Previous rodent examples [11], [19], [20] add to a growing literature supporting the physiological and neurological processes underlying allostatic orchestration. Nevertheless, allostatic prediction mechanisms had not been empirically evidenced until recently. Ian R. Kleckner et al [5] have described a large-scale brain system supporting allostasis and interoception in humans based on the analysis of multiple functional magnetic resonance imaging samples and track-tracing studies of macaque monkeys. Images suggest that the allostatic-interoceptive system is allocated in both the default network and the salience network, with areas between the cerebral cortex and the subcortical (e.g., hypothalamus) and brainstem structures, previously known to control the body's internal environment. Moreover, both networks are situated within the most densely connected parts of the brain, suggesting that the allostasis-interoceptive system is at the core of the brain's computational architecture [7][8].

It is thought there is a hierarchical arrangement in brain architecture for predictive processing[6]. Its main components to achieve predictive regulation are described as follows: (1) Prediction signals generated through memory, or an internal model built on experience. (2) Incoming sense data from the body which are encoded as the difference between predictive sensory inputs (prediction errors) and feedforward signals (inputs coming from the external environment) and (3) precision signals which modulate the strength and durability of predictions and prediction errors, and their ability to access motor control and influence. According to Yuta Katsumi et al[6] prediction signals are likely to begin as visceromotor control signals in a/dysgranular limbic cortices within the intrinsic allostatic-interoceptive system. Regions such as the anterior mid-cingulate cortex, ventral anterior insula/posterior orbitofrontal cortex, are those responsible of sending prediction signals that then descend to subcortical and brainstem nuclei, which help regulate the body's internal milieu. Both regions, a/dysgranular -mainly related with visceromotor cortices and emotional processing- and the more granular ones - executive function –have functional and structural properties consistent with the flow of prediction and error signals.

These studies challenge the traditional view in neuroscience that described the regions of interoception and those in charge of sending visceromotor signals as two segregated systems, rather than two intimately integrated ones. Furthermore, it defies pre-existing theories about the brain's functions matching almost exclusively to brain regions, describing the brain as a domain general organ since regions that control inner body physiology lie in networks that also support emotion, memory, and cognitive control [7]. Having such recent biological support of predictive allostasis encourages the development of simulations that could potentially foster its understanding. As a brain function, allostasis belongs to a myriad of functions that are currently being studied and simulated and having reliable models that reflect those functions could contribute to better comprehension of anticipatory mechanisms for regulatory control.

The simulation proposed in this study uses feedback and feedforward controllers,along with a neural attractor model, all of which will be further described in detail, but which are useful in representing allostasis as orchestration and prediction. On one hand, attractors are involved in the sequentiality of allostasis, this is which need should be prioritized when a conflict emerges and on the other hand, the feedback plus the feedforward module simulate both the reaction and anticipation from regulatory control.

It is hypothesized that the agent without predictive allostasis will manage homeostatic control and conflict emergence in a poorer way, in contrast with a predictive allostatic agent. That is to say that the non-predictive agent will tend to experience higher homeostatic error, meaning the difference between the desired value and actual value of the system for either thirst and internal temperature will be higher in comparison to the predictive agent.

2. Method

Anticipation of future disturbances in some animal and human brains is possible due to the constant communication between the default mode network and the salience network. The first one has been associated with tasks such as remembering the past and projecting into the future; the latter, is related to integrating internal sensations with decision making [5]. This constant unconscious and conscious reminiscence to previous experiences in order to predict possible disturbances with sensory information from within and outside the body, characteristic of the allostatic-interoceptive system, are intended to be partially replicated in the present simulation by using an allostatic feedforward controller over a homeostatic feedback one, with the purpose of comparing the agent's performance under predictive allostasis versus reactive homeostasis.

Consequently, to compare whether simulating the predictive feature of allostasis on a virtual agent generates more efficient regulation in contrast to non-anticipatory models of regulatory control, the present research aims to compare a model of regulatory control built only with a feedback controller, in which the anticipatory mechanism is absent, versus an allostatic model of regulation in which both a feedback and feedforward controllers are used to mimic predictive regulatory control for both single and competing drives.

In the present simulation, an agent will be placed under changing temperatures across time to mimic seasonal changes, with two needs to satiate: thirst and internal temperature. External temperature will be used as a cue to anticipate extreme internal temperatures, more specifically temperatures that are low in relation to the ideal value of internal temperature.

The guiding questions for the research address two stages of anticipatory control - single drive anticipation and multiple drive orchestration. That is to say, how values of homeostatic error are affected when the agent is able to anticipate upcoming disturbances in one and in both of its homeostatic sub systems.

It is expected that the homeostatic errors are significantly lower when the agent has the capacity to anticipate future disturbances in homeostatic systems compared to a non-predictive agent, due to the predictive nature of the feedforward controller over the feedback one. Thus, the proposed hypotheses for the current study are as follows:

- H1: When integrating the feedforward module as anticipatory allostatic control for a single drive, the synthetic agent shows reduced homeostatic error on average as a result of predicting future disturbances, in comparison to an agent in a simulation without anticipatory allostasis, unable to predict.

- H2: When integrating the feedforward module as anticipatory allostatic control over a model of competing drives, the synthetic agent will show less error and greater stability in addressing competing needs, compared to an agent in a simulation without anticipatory allostasis, unable to predict.

2.2 Environment:

The agent is faced with 2 emerging needs, thirst and internal temperature, which can be satiated at contrary locations from the environment. Two gradients were used in the simulation, one for temperature and the other one for thirst and the task for the agent is to satiate both needs as they rise.

Temperature gradient:

The environment of the simulation recreates changing temperatures of day and night cycles in the outer world, extending the gradient-based method introduced by Sanchez-Fibla et al [20] for a spatial navigation task.

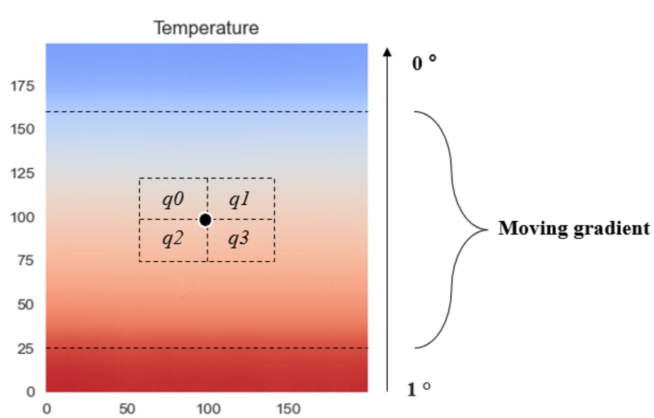

Figure 3: Temperature gradient. *The bottom of the matrix represents high temperatures while the top represents low ones while the middle consists of a moving gradient, with sorted values between 0 and 1. The*

black dot is the location of the robot, containing an actual temperature value and four quadrants of the local view.

Figure 3 describes the temperature gradient, a 200x200 matrix, corresponding to the arena size in which the agent performs the regulatory task. The matrix behaves dynamically, the lower part of the gradient represents a high temperature zone, in contrast with the upper part of the gradient which symbolizes a low temperature one. Across the matrix, a smaller gradient of size 64*200 moves along the y axis with sorted values between one and zero, meaning building cells from the matrix contain a specific temperature value. With every timestep the gradient shifts towards the top at max 130 on the Y axis of the matrix, allowing it to be filled with rows of ones when mimicking day time and falls down to 0 along the y axis, filling the matrix with rows of zeros when simulating night time.

The environment's mean temperature is 0.4 at the beginning of the simulation and continues its trajectory as a sinusoidal curve with max value of 0.8 and min value of 0.2. These changes in temperature are displayed in blue and red colors. The temperature of the environment mimics two day and night cycles reflected in the colors of the matrix, the lower the temperature the more blue in the grid, the higher the temperature, the redder.

Because the simulation consists of a changing temperature, the agent can perform drive reduction of homeostatic errors for temperature across the matrix. Moreover, because of the distribution of the values across it, low zones of the matrix will correspond to the coordinates in which drive reduction for low temperatures can happen.

Thirst gradient:

Figure 4 describes thirst reduction gradient, which works similarly to the gradients described in Sanchez-Fibla et al[20], the gradient for thirst corresponds to a map of orientation towards the satiating zone, meaning arranged values between 0 and 1 fill the grid on a radius of 180 from highest point for satiation for thirst which corresponds to coordinates x = 15, y = 185 in the matrix. It is relevant to notice that contrary to the temperature gradient, the one for thirst has fixed values across the simulation.

Satiating zones to the agent's needs in the simulation are situated opposite to each other across the environment, thirst drive reduction is performed at the top left of the field while cold temperatures are compensated at the bottom as can be seen in figure 4.

(a) Thirst reduction (b) Temperature regulation

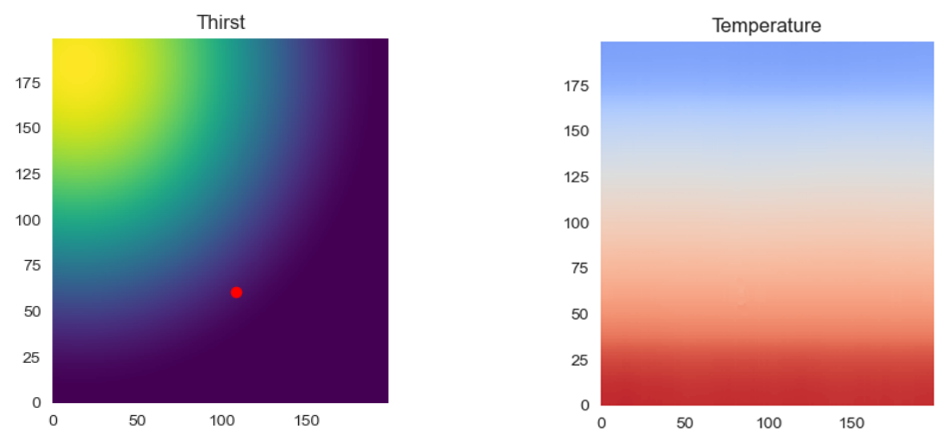

Figure 4. Gradient distribution *where (a) thirst reduction indicates where in the gradient (coordinates y: 15, y: 185) does the agent satiate thirst, while (b) characterizes where in the gradient the agent performs cold reduction at the middle and bottom of the grid.*

2.2.1 Sensing the environment and navigation:

The agent has no access to the workings of the gradients described above, and its navigation is following a local perception of the gradients; this local view involves four quadrants (upper left, upper right, lower left, and lower right) shown in image 3. Each quadrant includes the agent's adjacent cells that form a smaller 4x3 matrix q0, q1, q2, q3. The mean values of the four quadrants make up the local view of the agent, which in the simulation represents the actual value of both thirst and internal temperature.

Quadrants are a reference point for the agent's navigation, they are determinant in quantifying further measurements of direction, for further information on navigation refer to Sanchez-Fibla et al [20]

2.3 Regulatory control:

The goal of the simulation is for the agent to anticipate relevant deviations in values for thirst or internal temperature before they happen and act accordingly. Anticipation is achieved due to the integration of an allostatic controller module over a homeostatic one. Figure 4 describes the diagrams of the compared strategies for regulatory control, one (i) a reactive feedback controller, and the other one, (ii) a predictive feedforward one, which will be further described below.

(i). Homeostatic reaction: Without feedforward controller

(ii) Predictive allostasis: Feedforward controller

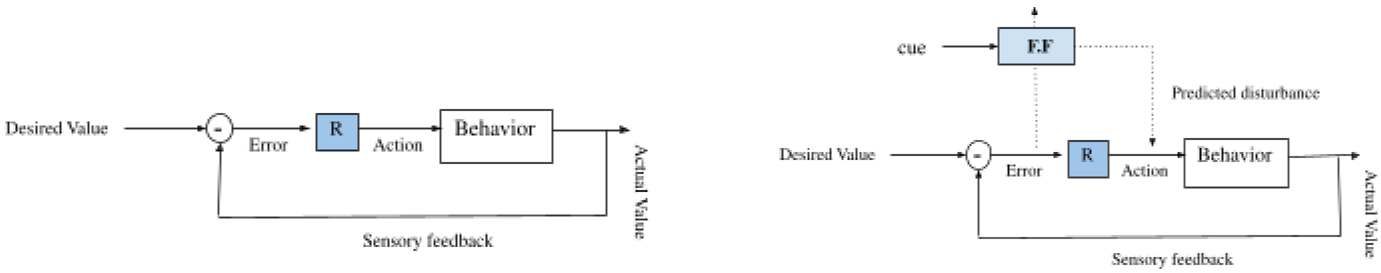

Figure 5. *Allostasis anticipation in comparison with homeostasis, or non-predictive regulatory control.(i)The homeostatic error is converted into responsive behavior by the feedback controller.(ii) A feed-forward anticipatory action associated with the cue (temperature from the grid) is acquired by the agent, and therefore a prediction of the expected impact issued by the changes in the signal temperature triggers a compensatory response in an anticipatory manner.*

2.3.1 Feedback controller:

Allostasis can be defined as a dynamic system in which emergent needs such as internal temperature or thirst are subject to continuous change. However, regulatory control of emergent needs tends to generate responses to minimize changes in the system, so that certain parameters in the internal milieu are maintained.

Such regulation from deviation is done through a feedback controller, which generates correcting actions on the difference between the desired and actual value of the system.[22]

The workings of the homeostatic systems are similar to Sanchez-Fibla et al [20], in the sense that they are both equipped with a constant discount of 1e-3 unless the error, which is the difference between the desired value and the actual value is less than 0.2, an error this low indicates the agent is on a location at the gradient in which the need is satisfied and will gain a bonus of ten times the value of discount.

The way in which the simulation operates is by using two simple feedback mechanisms, described as follows:

if error > 0.2 then constant discount to aV for the homeostatic system.

if error < 0.2 then bonus is added to aV for the homeostatic system.

$Error = desiredvalue - actualvalue$

$discount = 1e - 3$

$bonus = discount * 10$

dV = Desired value of the system, which is at constant 1

aV= Actual value of the system at every timestep

For the present simulation when $Error$ > 0.1 the agent engages in a compensatory action, for example if $aV\ Internal\ Temperature = 0.3$ at a certain point across the simulation, an $Error$ of 0.7 will be generated, and since $error >$ 0.2, a compensatory behavior will be performed. This means that the agent will tend to move towards regions in which the temperature is higher compared to the temperature values of its current location. Nevertheless, the simulation is built with two feedback controllers, one per drive. This means that whenever both needs have an error larger than 0.2, a competition on which drive to satiate will emerge. The dynamics of conflict resolution will be further described in section 2.2.3: Implementation with attractors in orchestration and anticipation.

In the case of the simulation, internal physiological states of the agent are encoded as vectors of actual values, resulting from the local views of the agent across the simulation. Thirst and internal temperature can be related to a physical quantity, such as the agent's internal temperature or the amount of water taken by it. Both vectors (thirst and internal temperature) evolve throughout the simulation according to the following:

> Constant discount of 0.001 in homeostatic levels per episode for both temperature and thirst, unless the error is < 0.2
>
> When error is <0.2 , it means the agent is closer to the satiating source, and therefore a bonus of (discount*10) to the Actual value of the drive is added.

Quantities can not be negative or bigger than one for either drive. Therefore values smaller than 0 are set to zero and those higher than 1 are set to 1.

2.3.2 Feedforward controller:

Since the reactive nature of the feedback controller does not allow the system to generate compensatory actions before an error is sensed, an integration of a feedforward controller is needed to respond predictively to the disturbance.[22]

The effect of the disturbance is reduced by measuring the error and creating a control signal directed towards the feedback module to counteract it as seen in figure 4. The used feedforward controller follows Maffei et al [23] cerebellar model's method with slight changes described below.

The system receives a single sensory input, a sinusoidal shape signal representing external temperature in day and night cycles, that is expanded into (n=100) different signals or bases, each base corresponds to the convolution of the sensory input (external temperature) with an α signal that can be formulated as two serially linked leaky integrators with identical time constants. For a particular basis, its output value is generated as follows:

$$z_j(t+\Delta t) = \gamma_j z_j(t) + \zeta_j x(t)$$

$$p_j(t + \Delta t) = \gamma_j p_j(t) + z_j(t)$$

An expansion of the original signal $x(t)$ into a series of bases is achieved. The second processing step consists in mixing the obtained bases with a weight vector w(t) that projects to a population of units whose outputs are delayed to different degrees (within a predefined range), with their sum at each timestep generating the output signal of the feedforward module ($ff(t)$).

$$ff(t) = w(t)^t p(t)$$

Where $p_{(t)} = [p1_{(t)}, p2_{(t)}, p3_{(t)}]^t$ is the vector of the bases. The weight vector is adaptively set by means of an LMS (Least Mean Squares):

$$w(t + \Delta t) = w(t) + \beta\epsilon(t)p(t - \delta)$$

Where ϵ(t) is an appropriate error signal that is used to update the weights. This corresponds to the homeostatic error for the homeostatic system, either thirst or temperature or both when two feedforward controllers are added. The eligibility trace is implicit in the use of a delayed copy of the bases activity $p(t - \delta)$. To do the weights update, the error is associated with an activity on the basis signals δ seconds ago. It is assumed that activity at time $t - \delta$ is the one that should have been used to trigger a reaction with sufficient anticipation to cancel the error at time t. Each delay unit in the population has a different δ so that the delay for the eligibility trace matches the delay of the unit's output itself. In this way, the unit that has a delay that matches best the actual difference between input and error will get a higher increase in weights, so that the delay is implicitly learned.

2.3.3 Implementation with attractors in orchestration and anticipation

When competing drives emerge, a conflict resolution needs to be performed by the agent. To do this, an attractor model developed by Amil & Vershure[22] used to simulate the activity of two competing neural populations during a perceptual decision-making task was used.

The original attractor was slightly modified, and additional input values from the feedback and feedforward controllers were incorporated. The input of the decision making layer is the error value for thirst and temperature coming from the feedback controllers, times the output from each added feedforward controller, on the multiple drive condition.

For the single drive condition the output of the feedforward controller is multiplied times the error only in *I2*.

$$I1 = (Errorthirst * 10) * ff(t)$$
$$I2 = (ErrorTemperature * 10) * ff(t)$$

$$\tau dU1(t)dt = - U1 + f(w + U1 + I1 - Qw - U2 - (1 - Q)w = f(U1 + U2)) + \sigma\xi(t)$$

$$\tau dU2(t)dt = - U2 + f(w + U2 + I2 - Qw - U1 - (1 - Q)w = f(U1 + U2)) + \sigma\xi(t)$$

Where f (x) is the logistic f –I function,

$$f(x) = Fmax/1 + e(- (x - \theta)/k)$$

Such values introduce a bias in the process of conflict resolution and therefore, it is expected that the agent addresses the need with higher values resulting from the attractor.

2.4 Experimental design

The implementation of the study took place by running two different simulations, one with a non-predictive agent and another one with a predictive one, which correspond to the non feedforward and feedforward conditions. Each simulation was performed 50 times over a period of 90.000 timesteps every time.

The agent starts at a random position at the beginning of the simulation on both conditions and with equal dynamics on each homeostatic systems or feedback controller and actual values for both homeostatic systems are initialized at desired value 1.

At the end of each simulation, information of the agent's behavior and internal states was saved on CSV files which were used later for data analysis. The logged information from every single simulation includes: the trajectory of the agent, the actual values and the error for each homeostatic system aside from the mean temperature of the dynamic gradient and the output of the feedforward controller. Data analyses for both conditions were carried out with the purpose of comparing performance. Further information regarding data processing is described below.

2.5 Data analysis:

Once the feedforward controller is implemented, a comparison of the responsive feedback controller vs the predictive one will be made by contrasting error values and agent's behavior on both non-feedforward and feedforward conditions.

2.5.1 Evaluation metrics:

To test the proposed hypotheses for the study the following variables are going to be measured for both the non-predictive and the predictive allostatic models on the two proposed conditions, which were single and multiple drive anticipation.

Feedforward single drive:

Average internal temperature during the simulation:

Average internal temperature is the sum of the values within $aV\_internal\_temp\_list$,a list that contains the aV(actual value) of internal temperature of the agent over the n episodes of the simulation, divided by the number of episodes.

$$\mu ActualValueInternalTemperature = \frac{\sum_{i=0}^{n} aV_i}{n}$$

Where n represents the number of episodes. If $\mu ActualValueInternalTemperature$ were to approach one it would mean the agent's regulatory actions were satisfactory and unbalance in the system was rare, in other words, it indicates the agent was almost never too cold. In contrast, if the value were to approach zero it would mean the agent did not react to the disturbances of the environment and therefore it was constantly in a cold state while in the simulation.

Homeostatic error:

The average of the difference between desired and actual value for each drive, represents the homeostatic error across the simulation. In other words, how far was the agent's internal temperature from the desired value across the simulation. The homeostatic error is measured by the sum of the differences between 1 and $aV\_internal\_temp\_list$, a list with the actual values of internal temperature, divided by the number episodes.

$$\mu Errorinternaltemp = \sum(dV - aV)/n$$

Where n represents the number of episodes. In this case, if $\mu Errorinternaltemp$ approaches one, it suggests the agent could not properly address the disturbances in temperature, and therefore experienced constant deviation from the desired value, that is to say, the agent was constantly experiencing coldness.

Multiple drives:

The measured variables for multiple drives are efficiency, fairness and stability, which will be later compared to the non- predictive agent.

Homeostatic error:

The aforementioned mentioned measure of homeostatic error for internal temperature will be used for both drives under this condition.

Efficiency:

Measures how effectively the agent satisfied the disturbances across the simulations. If the efficiency value is close to 1, it means that the agent was efficient since almost no disturbance for either drive (thirst or internal temperature) was experienced across the simulation.

Efficiency is measured by averaging the mean values of $aVInternalTemperature$ and $aVthirst$ across the simulation.

$$efficiency_i = \frac{\mu ActualValueInternalTemperature + \mu ActualValuethirst}{2}$$

Fairness:

Represents the balance between the two homeostatic needs. For instance, if the agent responded fairly to both needs, or if there was a more prevalent drive addressed across the simulation.

Fairness is measured by subtracting 1 from the distance between the mean values of $aVInternalTemperature$ and $aVthirst$ across the simulation.

$$fairness_i = 1 - (\mu aVInternalTemperature - \mu aVthirst)$$

When fairness approaches one, it indicates that both drives were treated equally and therefore a fair conflict resolution took place. However, if fairness tends towards zero, it shows an unfair conflict resolution which leads to satisfy one drive over the other.

Stability:

Measures how well the agent maintained homeostatic regulation for both thirst and internal temperature across the simulation. Stability is measured by subtracting 1 from the squared difference between two vectors corresponding to the desired values and actual values of the homeostatic systems.

$DV = [1,1]$

$Actual\ values\ =\ [ActualValuesThirst][ActualValuesTemperature]$

$$Stability\ =\ 1\ -\ (DV\ -\ Actual\ values)^2$$

2.4.2 Comparison between non-predictive vs predictive allostatic regulation

After computing the evaluation metrics results will be analyzed for both the responsive feedback controller vs the predictive feedforward controller models, when presented with single drive and multiple drive disturbance.

3. Results

Results are divided into two sections, the first one describing single drive prediction in comparison to a non-predictive agent and the second one reporting the dynamics of the agent when multiple drive prediction takes place.

They encompass the average of 50 simulations per condition with 90.000 timesteps per simulation.

3.1 Single drive prediction:

Single drive prediction required the use of one feedforward controller, added as a layer only over internal temperature and not over thirst.

The measurements taken for predictive and reactive single drive fulfillment on both non-feedforward and feedforward conditions were the homeostatic error and actual value of each homeostatic system. These metrics indicate how the agent addressed the emergent needs such as thirst and internal temperature under both feedforward and non-feedforward conditions.

Figure 6 describes the behavior of both homeostatic subsystems under feedforward and non-feedforward conditions. The figure shows how under the feedforward condition, internal temperature, on average, stays extremely close to one (0.9) during the simulation while thirst stays almost at constant zero (0.03), revealing a significant bias towards satiating internal temperature, while almost neglecting thirst.

When comparing the actual values for internal temperature of the agent on both conditions the feedforward one had a higher mean value (0.9) compared to non-feedforward (0.6), reflecting once more how success in achieving constant desired value for temperature in the single drive implementation comes along with ignoring thirst during the simulation.

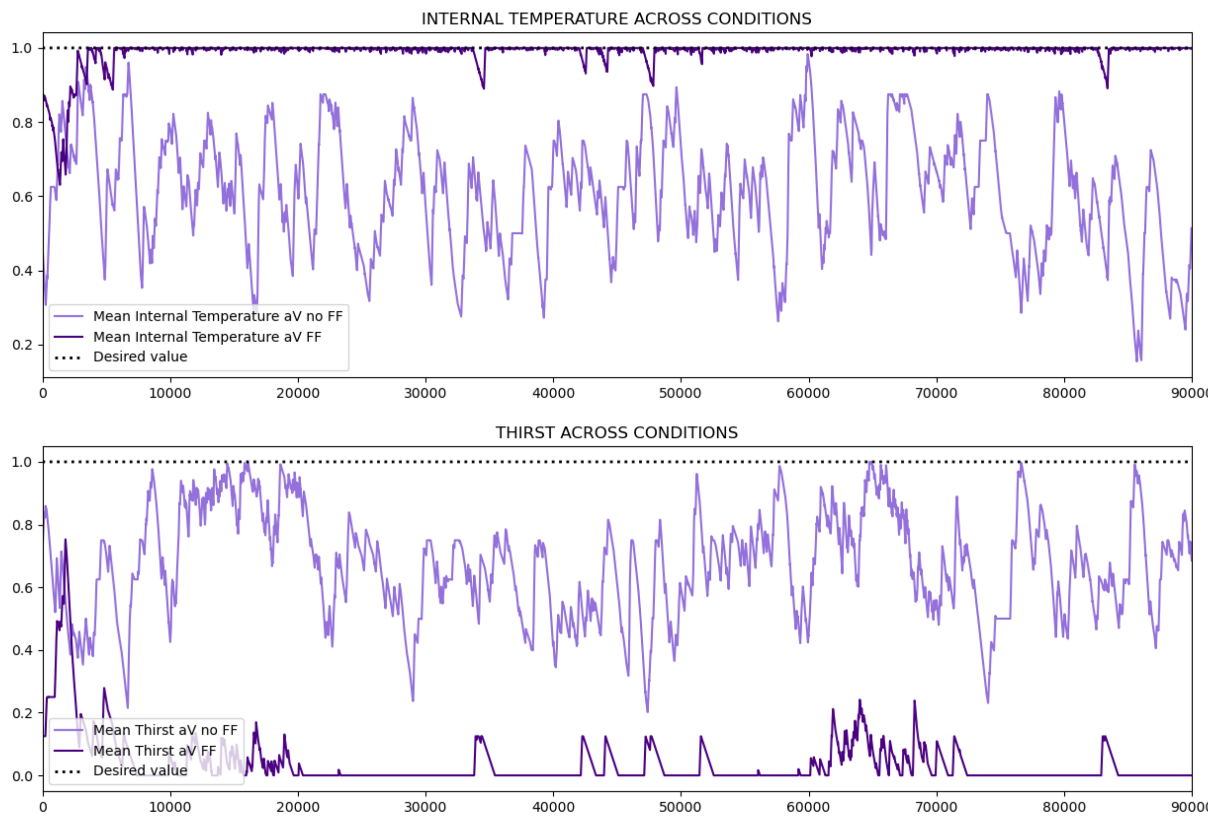

Figure 6. *Actual values for thirst and temperature under both feedforward and non feedforward conditions. Temperature is closer to one on the feedforward condition while thirst is closer to zero. Under the non-feedforward condition values for temperature and thirst remain oscillating between one and zero.*

Complementary to the results related to the actual values of both homeostatic needs previously described. Figure 7 shows how the error for internal temperature decreased significantly upon the introduction of the feedforward controller..

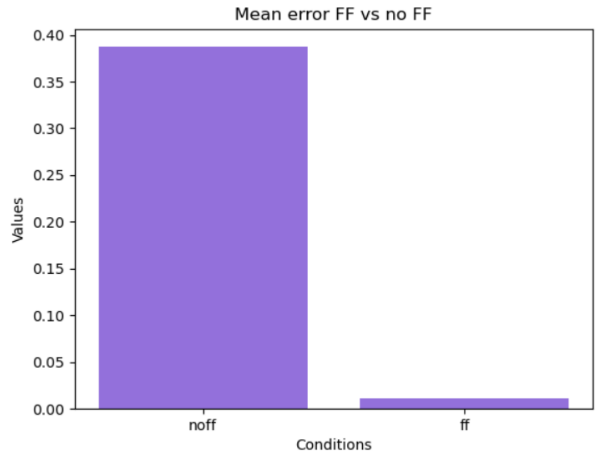

***Figure** 7. Average error of internal temperature. For the feedforward condition it is 0.010 and for the non-feedforward condition 0.387.*

As stated before, when only one feedforward was added over internal temperature, the tendency of the agent was to prioritize this drive over thirst by staying at almost constant desired value, resulting in a significant reduction of the homeostatic error. Behavior of the agent can be clearly seen in figure 8. Here, the heatmap indicates how the agent roams more frequently around the satiating zones for temperature, which correspond to the middle to bottom zones of the grid, the lowest part being the warmest.

The reduction in error was the product of an emergent bias towards satiating temperature, explained by a constantly increasing input value for internal temperature drive in the conflict resolution layer once the feedforward controller was added, which generated the behavior from figure 8.

Although error was reduced for the drive with the added feedforward layer, the system did not act efficiently in the sense that thirst was ignored throughout all trials with an actual value staying at almost zero and no satiating behavior coming from the agent.

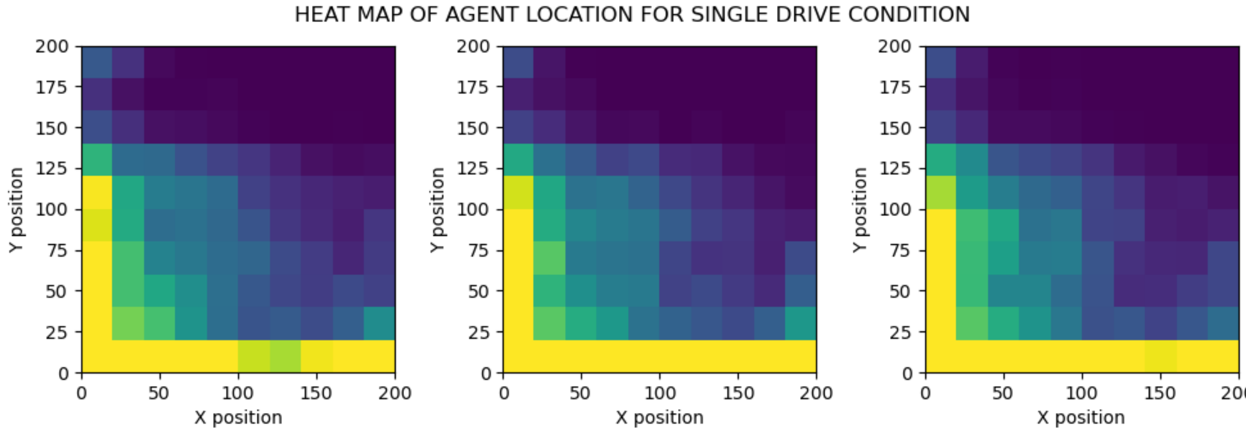

Figure 8. *Heatmap of agent location with one feedforward controller anticipating temperature. Lighter parts correspond to the most frequently visited parts from the matrix contrary to the darker ones.*

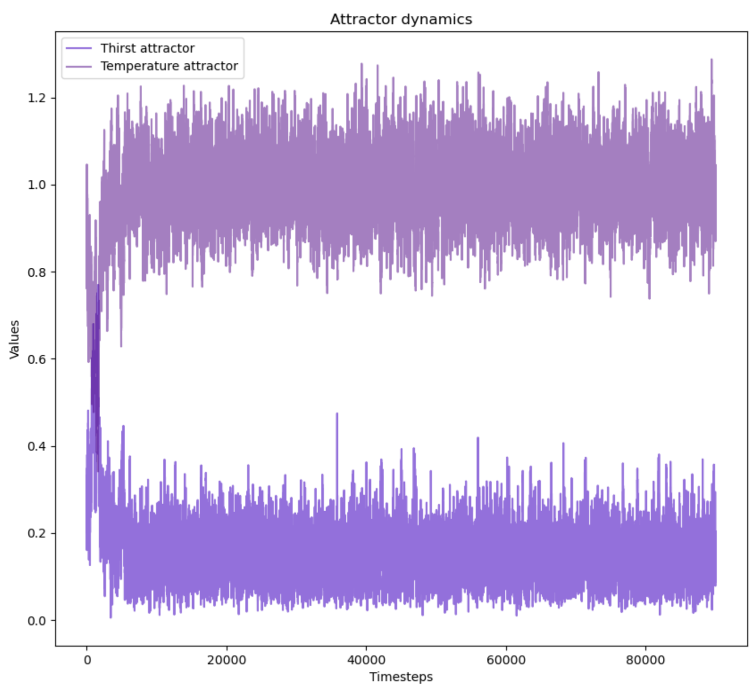

Figure 9: *Behavior of the attractors for both thirst and temperature at the decision making layer.*

Figure 9 shows the behavior of the attractors for both thirst and temperature when one feedforward controller was added. It is clear how the output of the temperature attractor overrides the one of thirst throughout the simulation. This happened due to the addition of the feedforward output only into the input *I2,* corresponding to temperature from the attractor model, which generated an imbalance in the input values and therefore a bias towards satiating temperature.

3.1 Multiple drive prediction

The measurements taken for multiple drive prediction on both non-feedforward and feedforward conditions were: homeostatic error, efficiency, stability and fairness.

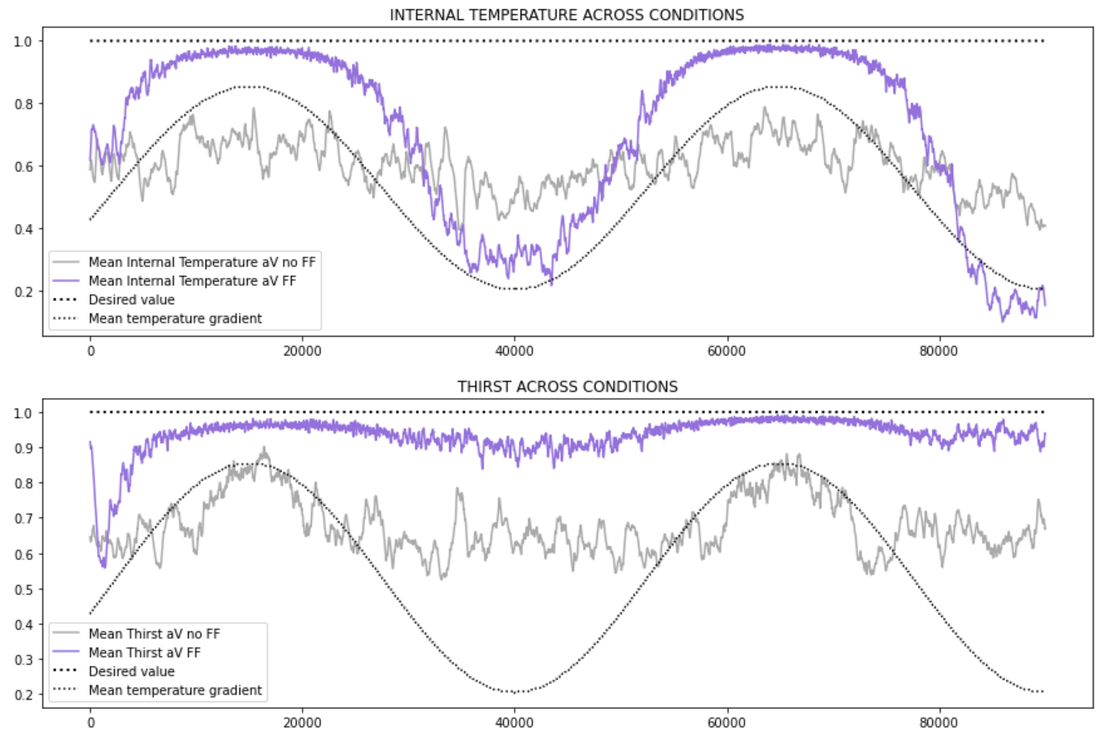

Figure 10: *Actual values for both thirst and internal temperature under feedforward and non-feedforward conditions.*

Figure 10, describes the changes in actual values of both thirst and temperature across the simulation, showing a higher tendency towards the desired value, more sensibility to external temperature and a bias towards constantly satiating thirst when in the feedforward condition. All of those emergent phenomena will be further analyzed at the end of the section.

The homeostatic error was found to be lower for both thirst and temperature under the feedforward condition. Figure 11 shows the distribution of the error for both drives, and a highly skewed distribution towards zero is present on the feedforward controller condition.

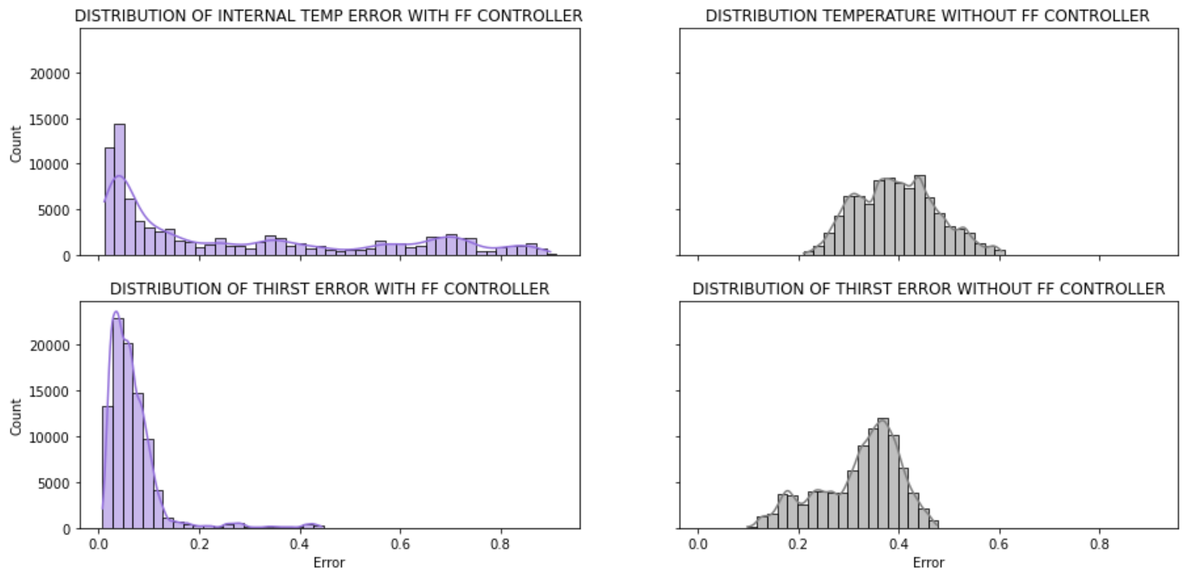

Figure 11. *Distribution of error for thirst and temperature under feedforward and non-feedforward conditions. The error distribution for the feedforward condition is highly condensed around zero in comparison with the non-feedforward one, showing how the error on the first condition is significantly lower.*

Figure 12 condenses the average of homeostatic error for both conditions. It is noticeable how the homeostatic error is on an average lower with the feedforward controller. In effect, the average of mean error thirst in the non-feedforward condition was 0.32 while 0.067 for the feedforward. Similarly, but with less significant difference, the error in internal temperature under the non-feedforward condition was 0.3968 and 0.2875 for the feedforward one.

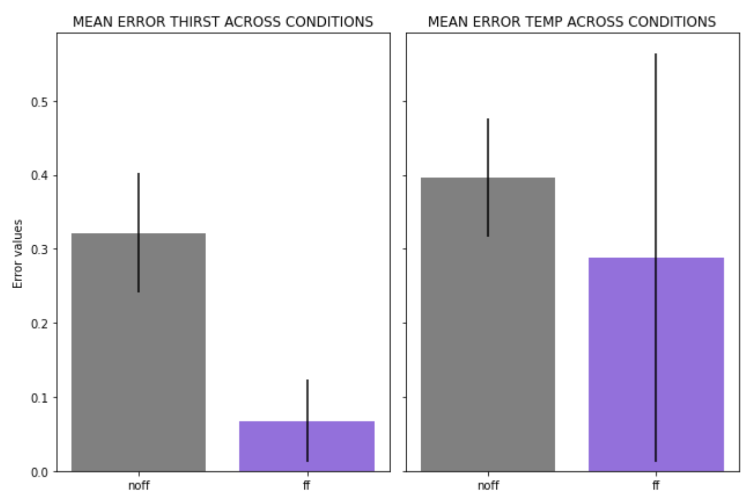

Figure 12. *Mean error for both temperature and thirst in feedforward and non-feedforward conditions with the standard deviation bars.*

Additionally, the standard deviation of the error for both thirst and temperature change across conditions. The standard deviation for thirst in the non-feedforward condition was 0.080 and 0.055 in the feedforward one. For temperature, the values were 0.079 and 0.276 correspondingly, which shows temperature's actual values had higher oscillation compared to thirst. Internal temperature was strongly tied to the temperature changes of the environment due to the agent's limited movement on the feedforward condition; more specific description on how the behavior of the agent affected its internal temperature will be further analyzed in the discussion section.

Below, a graph condensing the results for efficiency, stability and fairness for both conditions.
The results were taken by generating a selection of means over the 50 simulations on a window of 9000 timesteps. Further explanation on how these results were obtained is described in the evaluation metrics section.

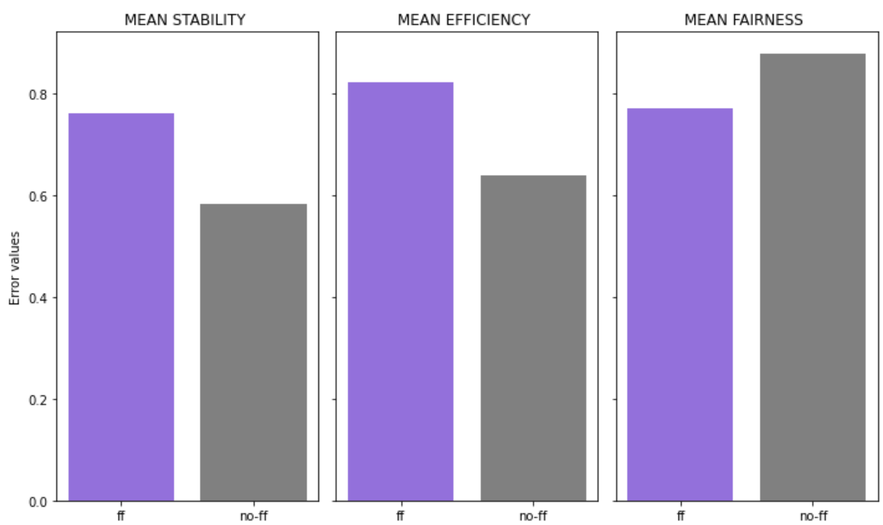

Figure 13: *Results for stability, fairness and efficiency when the agent is under feedforward compared to non-feedforward conditions.*

3.1.2 Efficiency

Efficiency reflects how effective the agent was in satisfying the needs as they emerged across the simulations. The closer to one, the more efficient in regulating both thirst and temperature. In this case, the efficiency was higher under the feedforward condition (0.8224) compared to the non-feedforward one (0.6406), meaning that the agent was more efficient in the first condition since on average almost no disturbance for either drive (thirst or internal temperature) was experienced across the simulation.

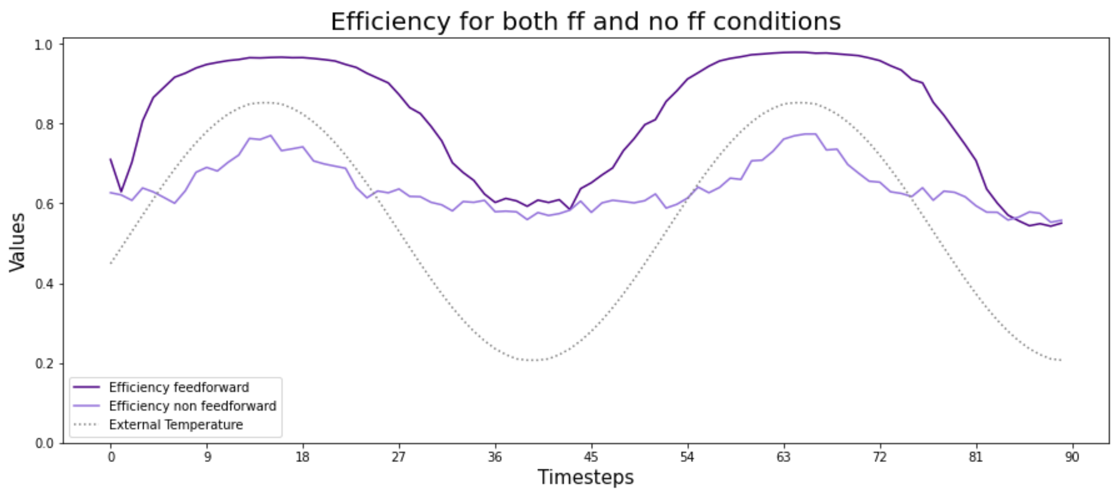

Figure 14. *Mean efficiency under 50 simulations with a window size of 1000 for both feedforward and non-feedforward conditions.*

3.1.4. Fairness

In regards to how fair the satiation of each drive was, the feedforward controller condition had a lower fairness on an average (0.778) compared to the non-feedforward one (0.903), indicating biased conflict resolution in which thirst is prioritized. Explanations on why this might have been the agent's behavior when under the feedforward condition are further explored in the discussion section.

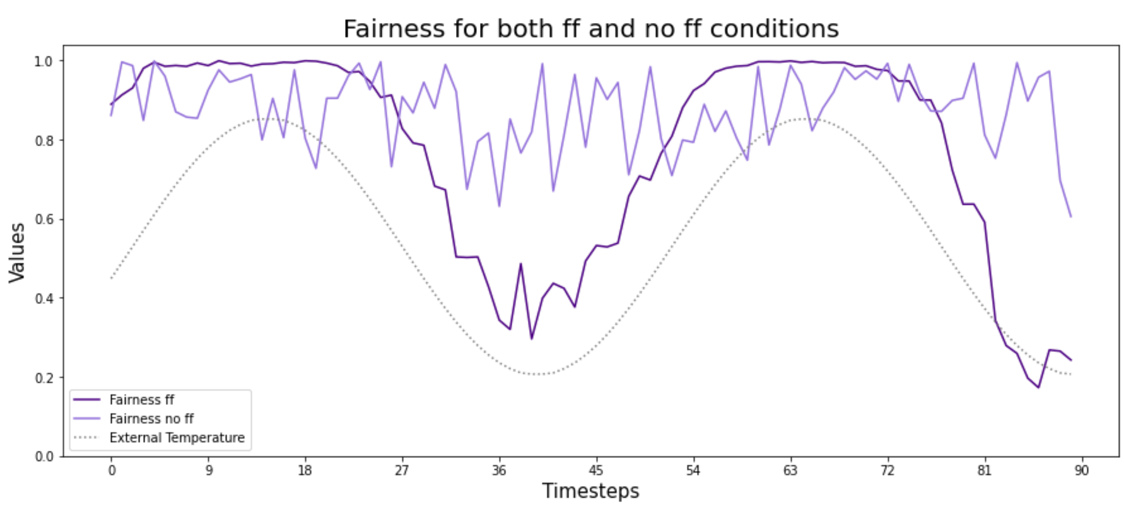

Figure 15. *Mean fairness under 50 simulations with a window size of 1000 for both feedforward and*

non-feedforward conditions.

It can be seen how almost all figures reflect the drop of internal temperature when the temperature of the environment decreases. As stated before, the feedforward condition generated higher stability and efficiency compared to the one without it, but less fairness due to the biased tendency aforementioned.

3.1.3 Stability

Stability reflects how well the agent maintained homeostatic regulation for both thirst and internal temperature across the simulation.It is a measurement that is sensitive to both fairness and efficiency as previously explained in the measured variables section.

When comparing conditions, the feedforward controller reflected higher stability (0.76) versus the non-feedforward condition (0.581). Showing that values for both thirst and temperature tended to oscillate more on an average under the non-feedforward condition than under the feedforward one. Nevertheless, the graph reflects a significant decrease in stability once the temperature of the environment is reduced and therefore the agent has to make a decision on which need to attend.

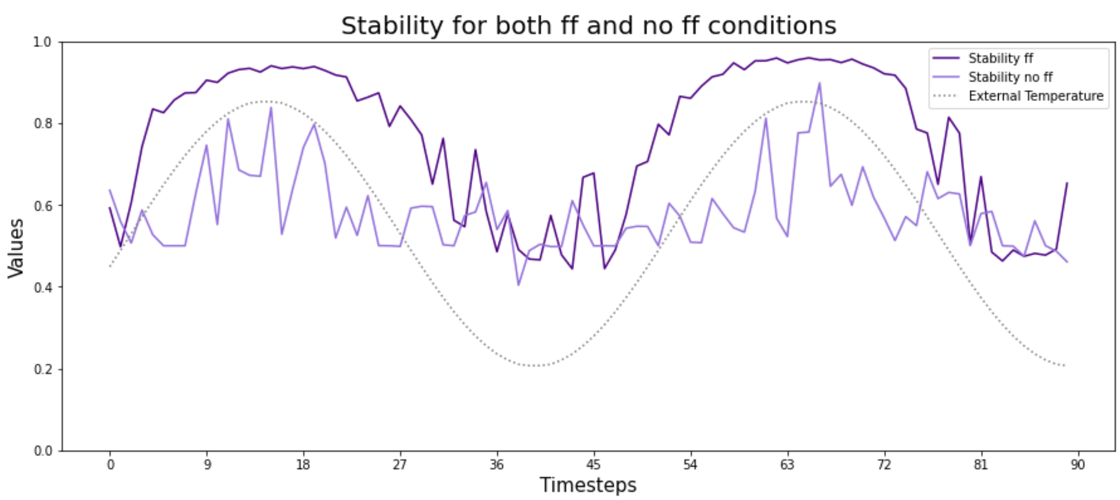

Figure 16. *Mean stability under 50 simulations with a window size of 1000 for both feedforward and non-feedforward conditions.*

3.1.5 Agent's behavior

It was interesting to notice the differences in the agent's behavior depending on the condition. Figure 17 shows the trajectory of the agent corresponding to the two conditions. In the non-feedforward condition, seen on the left side of the image, the agent moves across the x and y axes equally when trying to solve the task, whereas for the image on the right, the agent seems to move mainly across the y axis surrounding two points, one being the source of thirst relief at the upper left corner and the other one being middle left side of the gradient, which corresponds to high temperatures. A clearer depiction of behavior differences regarding the condition has to do with the movements of the agent in relation to the temperature of the gradient and they are shown in figure 18. Here the trajectory of the agent is mapped to the temperature of the environment. Red indicates higher temperatures while blue indicates low ones. The trajectory for the non-feedforward condition is very similar regardless of temperature of the environment, while when in the feedforward condition the behavior changes, the agent tends to stay in the y axis when the environment is warmer and roams more across the x axis when the external temperature decreases. Possible explanations for the differences in behavior are reviewed in the discussion section.

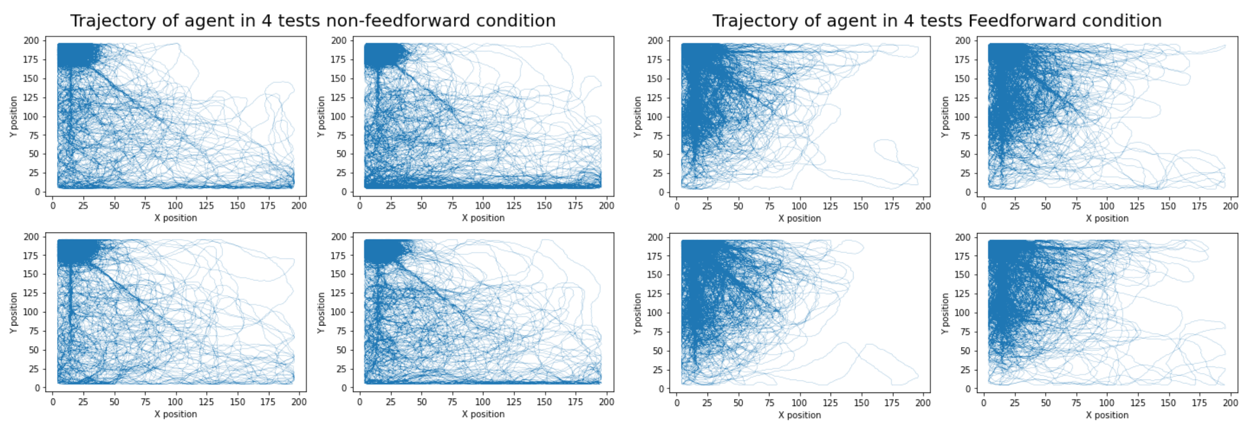

Figure 17. *Trajectory of the agent. The left side corresponds to the non-feedforward condition while the right side corresponds to the feedforward one.*

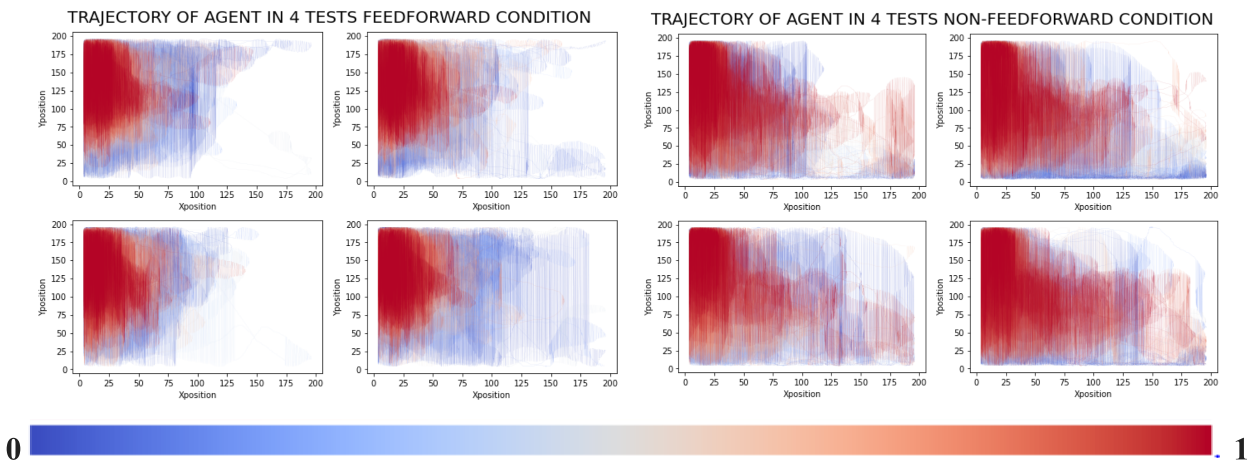

Figure 18. *Trajectory of the agent is matched according to the external temperature, or the temperature from the matrix, red color corresponds to higher temperatures(1) while blue colors correspond to colder ones(0). Left corresponds to the feedforward controller condition while right to the non-feedforward one.*

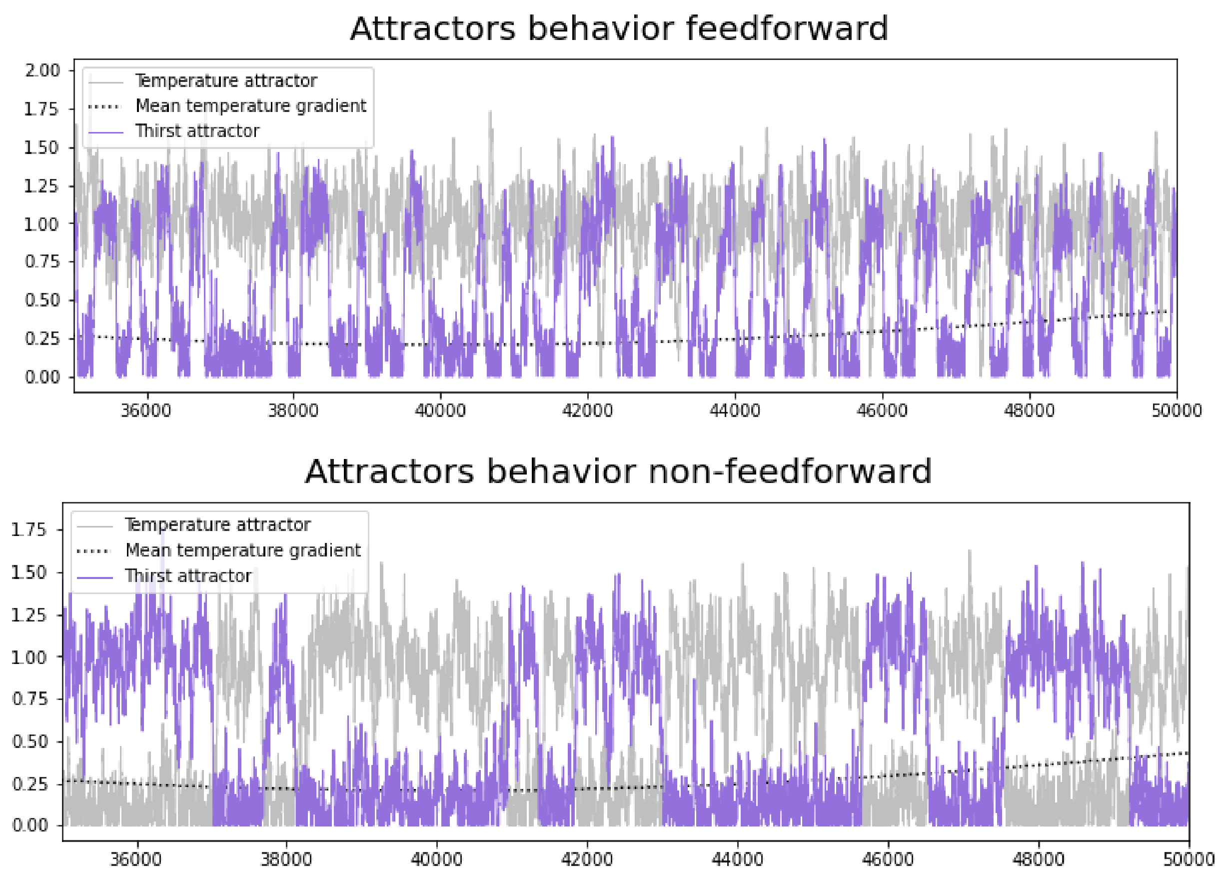

Figure 19: *Behavior of attractors for thirst and temperature in the decision making layer during low temperatures, timesteps 35000-50000. For both feedforward and non-feedforward conditions.*

The above figure depicts the competition happening between the output attractors for both temperature and thirst upon the addition of the two feedforward controllers. The image shows a more frequent change between attractors on the ff condition, compared to the non-feedforward one. Similar behavior is seen throughout the whole simulation, nonetheless selecting a specific period of time made the visualization of the phenomena clearer.

More frequent changes in the feedforward condition could be attributed to the addition of two feedforward controllers instead of one. The methodology used for the current study generated an unanticipated competition between the feedforward controllers, and as a result higher jumps on urgency for each drive in the decision making process of which need to attend.

4. Discussion

Previous results support the hypotheses from the study, since homeostatic error was reduced once the feedforward controller was added in both single and multiple drive conditions and more stability was achieved as shown in the results section for the multiple drive condition. Nevertheless, the reduced error found in the results can not be attributed to the simulation of allostasis's predictive feature, since the behavior of the feedforward controller was found not to be anticipatory due to methodological limitations when integrating the feedforward controllers into the model. Future methodological recommendations are given at the end of the section.

In the single drive condition, homeostatic error for temperature was significantly reduced once the feedforward controller was added. Reduced error was a product of an emergent bias towards satiating temperature, explained by an increased input value for internal temperature ($I2$) in the conflict resolution layer, which generated the behavior from figure 8, in which the agent stays at low zones from the matrix.

Even though the previous results were expected because only one of the needs was equipped with a feedforward controller, it is relevant to highlight that they do not correspond to the dynamics of allostasis, since orchestration and prioritization of a highly deprived need, in this case thirst, was almost nonexistent during the simulation.

Because of the lack of orchestration in the first scenario it became relevant to add two feedforward controllers, one per need, and hence the second hypothesis, which stated that the error would be reduced for both drives and that the addition of a feedforward controller would generate higher stability of the regulatory system.

In regard to the results from the second hypothesis there are several remarks. In the first place, as shown in the results section, when integrating the feedforward module as anticipatory allostatic control over a model of competing drives, the synthetic agent showed less homeostatic error for both homeostatic needs under the feedforward condition as shown in figure 12. Nevertheless, the way the agent solved the situation did not turn out to be anticipatory. In terms of the tools used, the feedforward controller acts as an error corrector with the objective of keeping the actual values of the drive as close to the desired values as possible. To achieve the objective, the feedforward controller used in the simulation generated increasing output values that would correlate with the temperature from the environment, but would not correspond to a learning pattern, nor an anticipatory one.

Generating constantly increasing values turned out to be a good solution to minimize the error of the system, since homeostatic error was indeed reduced. Nevertheless this does not indicate anticipation, since output patterns of the feedforward controllers did not show similarity across day and night cycles. Once the feedforward controller learns to match the errors to the external temperature in the first cycle, the outputs are expected to be similar when exposed to the same temperature afterwards in the simulation. Nevertheless, the observed behavior in figure 20 shows a constant increase in output values of the feedforward controller on the second day and night cycle from the simulation, going against the expected learning pattern.

The increase in output values coming from the feedforward controllers might imply the need to further fine tune the model or the implementation with two feedforward controllers; details on methodological adjustments will be given later in the document. However, what holds relevance for the current study is that in the proposed implementation, the feedforward controller is not mimicking allostasis' feature of prediction. Nevertheless, it is solving the problem at hand in a different way and significantly better than the non-feedforward condition.

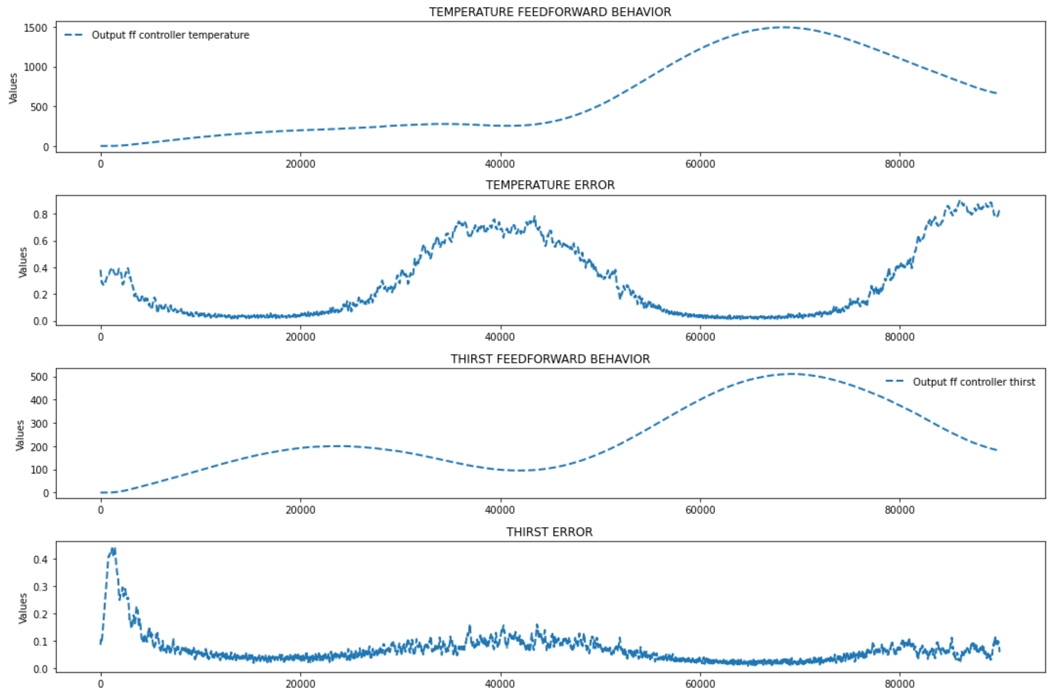

Figure 20. *Output values of both thirst and internal temperature feedforward controllers in dotted lines, besides the homeostatic error of each system across the simulation.*

Measurements for comparison such as stability, fairness and efficiency showed that the condition with the feedforward controller is more stable and efficient than the non feedforward one. This means the agent from the feedforward condition is on average more capable and efficient when it comes to maintaining both thirst and internal temperature near the desired values. These results are attributed to the addition of the feedforward controller and its impact on the decision making layer and thus, the behavior of the agent.

Once the feedforward controller is integrated to the decision making layer, the urgency of the needs tends to compete at a higher rate compared to the non-feedforward condition as can be seen on figure 19, which might be an explanation for the behavior of the agent on the feedforward condition, since having higher competition in the attractors results in reduced movement. Figure 17 and 18 portray the previously described phenomena, they explicitly show how less movement across the matrix results in higher markers for efficiency and stability and support the idea of limited movement being the result of higher competition in the attractors layer when the two feedforward controllers were added.

The way in which the agent with the feedforward controller satiates both needs involves less movement around the x axis of the environment and much more around the y axis as seen on figures 17 and 18. On the feedforward condition, the agent achieves close to desired values for both needs by staying at the top and middle points of the environment.

The behavior of the agent with the feedforward controller could be seen as less wasteful metabolically as apparently less roaming was needed to achieve regulation. Here, the agent does not move far away from the middle of the grid to satiate temperature when the environment is warm because there is no need to do so once the temperature increases, which happens in half of the total duration of the simulation. As thirst is satiated in the top left corner of the matrix, the agent is placed at a specific location in which both needs are highly satisfied.

Unfortunately, there was no measurement of energy consumption in the simulation, less roaming around the environment could potentially indicate less energy consumption to complete the task, one of the main traits of allostasis according to Sterling [17]. Because of this reason it is suggested that further work includes a measurement related to the energy expenditure of the agent across the simulation. This measurement would give better understanding of whether the addition of a feedforward controller is generating less energy expenditure throughout the simulation in addition to less homeostatic error.

Even though higher efficiency and stability were found for the feedforward condition when compared to the non-feedforward one, there is on average, a biased election towards satiating thirst across the simulation. Figure 10 shows the behavior of both homeostatic subsystems, clearly displaying how thirst tends to be constantly satiated compared to temperature, which indicates further need to calibrate and assess the integration of the feedforward controller with the objective of achieving anticipatory allostasis and a fair regulation, in which no need is left unsatisfied.

Further methodological recommendations include using a homeostatic function that instead of a constant decay uses a biologically grounded mathematical model of homeostasis that reflects changes in internal needs matching more accurately the behavior of the simulated needs. One limitation of the current homeostatic model is that no over-homeostasis can be experienced by the agent. That is to say, no overheating or filling of water can be ‘sensed’.

Additionally, in the multiple drive condition, the feedforward should have both subsystems in account and treat them as a whole, rather than generating a competition between them. This could be done by adding only one feedforward controller connected to the homeostatic systems to generate two outputs, one per need. This would imply modifications to the feedback controller and the current implementation that potentially could result in higher levels of fairness.

All of the limitations aforementioned are related with fine tuning of the current implementation, which imply a series of adaptations that both the feedforward controller and the homeostatic subsystems should undergo in order to comprehensively simulate the task of allostasis as it is described by [5][6].

Nevertheless, the current implementation does provide one of the first approximations to implement the analogy of control theory into the process of regulatory control and it is expected for more research to be built using feedforward controller systems to try to simulate allostatic regulation.

5. List of figures

6. References

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