

Theoretical Framework for Human-Like Robotic Taste with Reference to Nutritional Needs

Grzegorz Sochacki, Arsen Abdulali, Lucy Cheke and Fumiya Iida

Bio-Inspired Robotics Laboratory (BIRL), Department of Engineering, University of Cambridge, UK

E-mail: gks33@cam.ac.uk

Abstract. This paper contains a theoretical framework for an intelligent robot that can feed itself with organic matter and learns to like and want certain foods. Furthermore, being tied to the onboard generation of power, the robot's learning is grounded to physical requirements that need to be met for continued robot operation. We posit a system wherein the electrical power is generated by a microbial fuel cell(MFC), and the food value can be assessed by measuring the current generated. Interestingly, the MFC requires feed similar in many parameters to food preferred by most people with respect to parameters like salinity or pH. This property is theorized to be a good start for teaching a robotic chef human preferences. We also propose a circuit that injects additional current, simulating social cues for some foods, and effectively resulting in learning an acquired taste.

1. Introduction

Recent research on robotic cooking and electronic taste opens the possibility of robots entering the vast business of cooking and catering. Various types of electronic tongues and similar sensors are capable of feats like classifying wine age[1], finding pork contamination in mutton[2] and assessing fish freshness[3]. Moreover, the electronic taste has been used as feedback for a robotic chef, controlling the saltiness and texture of scrambled eggs[4]. Some approaches also use human taste to adjust robotic chefs' cooking[5].

This ability to implement taste for robotic chefs together with the low cost of robotic labour raises the possibility of producing cheap, individualized dishes. The major problem with the realization of this idea is machine learning for taste. Most capable models consist of large neural networks requiring sizeable labelled datasets. Taste factors such as the palatability of dishes are highly subjective and personal and thus cannot be objectively labelled. Furthermore, the structure of this label is undefined: A lack of exhaustive theory connecting measurable chemicals to notions of flavour and palatability limits precision, especially taking into account individual preference. This problem is not trivial to solve, but human chefs have the advantage of sharing in same preference spectrum as other humans, therefore making it easier to predict and accommodate these tastes. It may be the case that robotic chefs must thus be able to simulate client's preferences - as humans do - to excel in this function. The first step towards that goal may be the development of food preferences by the robot for themselves.

In this paper we propose a theory for robotic taste, taking inspiration from human feeding behaviour as shown in Figure 1. Moreover, we propose a robot that, using this theory, will develop its own subjective taste based on objective physical needs. For this thought experiment



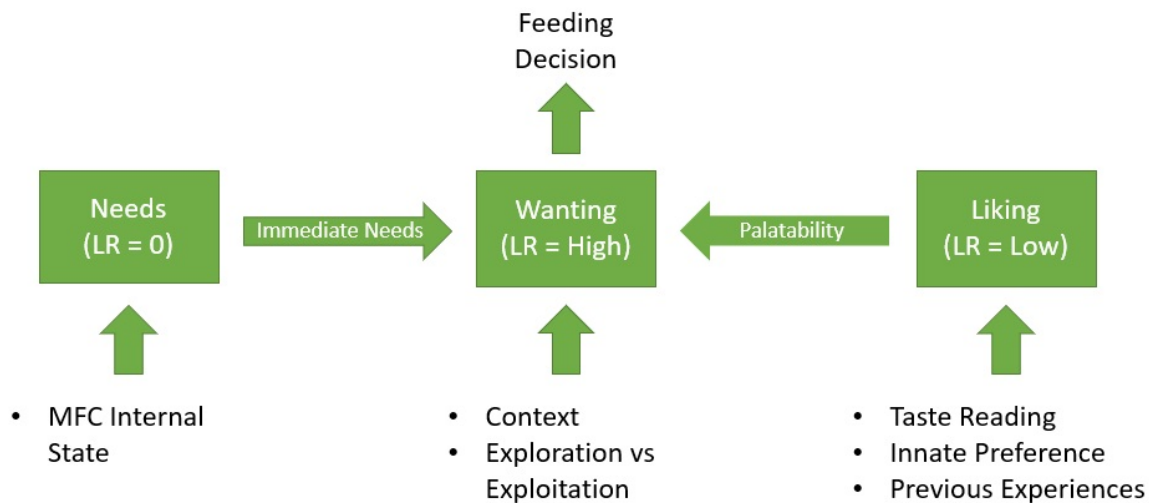


Figure 1. Schematics of bio-inspired tasting model. The model is grounded by the physical robot body that produces its own energy. Therefore, the body has needs, that need to be met to produce energy. It will also develop liking or preferences for certain foods based on their usefulness and rarity. Finally, it has a block called wanting that takes all the information together, and makes a decision specific to the current context.

we use a robot that uses a Microbial Fuel Cell(MFC) to generate its own power. A few of these kinds of robots have been constructed starting with Wilkinon's train[6] that was the first known prototype to operational systems like EkoBots[7]–[9]. Examples of these and more gastrobots[10], [11] are shown in Figure 2. This type of robot is a relatively new invention and few challenges are yet to be solved decisively[6]. We expand the gastrobot idea by putting the robot in charge of feeding (and thus powering) itself, based on sensors inside the MFC, its performance and sensors probing encountered potential fuel. This setup provides both interoception[12], and relevant tasting of food, allowing for the learning and development of associations between flavours and the impact these have on fundamental energy and nutritional needs, just as in the human body. The exact propositions for these sensors are discussed in the following sections.

This robot provides a minimal model of a body that has needs(energy production by MFC) and a way to feed itself based on the taste of potential fuel options. As we are primarily interested in taste we will assume a rather simple environment within which liquids are available as a "food" for the robot. The robot would also have the possibility to sample or taste the prepared foods and choose among them. We present a machine-learning approach that has access to the internal state of the robot to monitor its needs and learn based on them. The first part of the system is learning "liking" for various products. "Liking" is a stable context-general value describing the desirability of food. Therefore, it will be learned with low learning rate, based on the power production after the consumption. This system assesses how much the food is 'liked' based on the sensory stimuli from the tongue. Secondly, we introduce a "wanting" system, that provides a time-specific context-based motivational value behind the food. Computing this value considers all internal sensor measurements, tongue readings, and liking signals an input and decides on the next consumption. This system has a faster learning rate. Moreover, it indirectly affects liking by controlling the food intake, therefore the food exposure. Finally, we discuss the similarities between flavours preferred by the robot and those liked by most people and the possibility of exploiting the robot's acquired taste to adjust its liking towards those preferred by people.

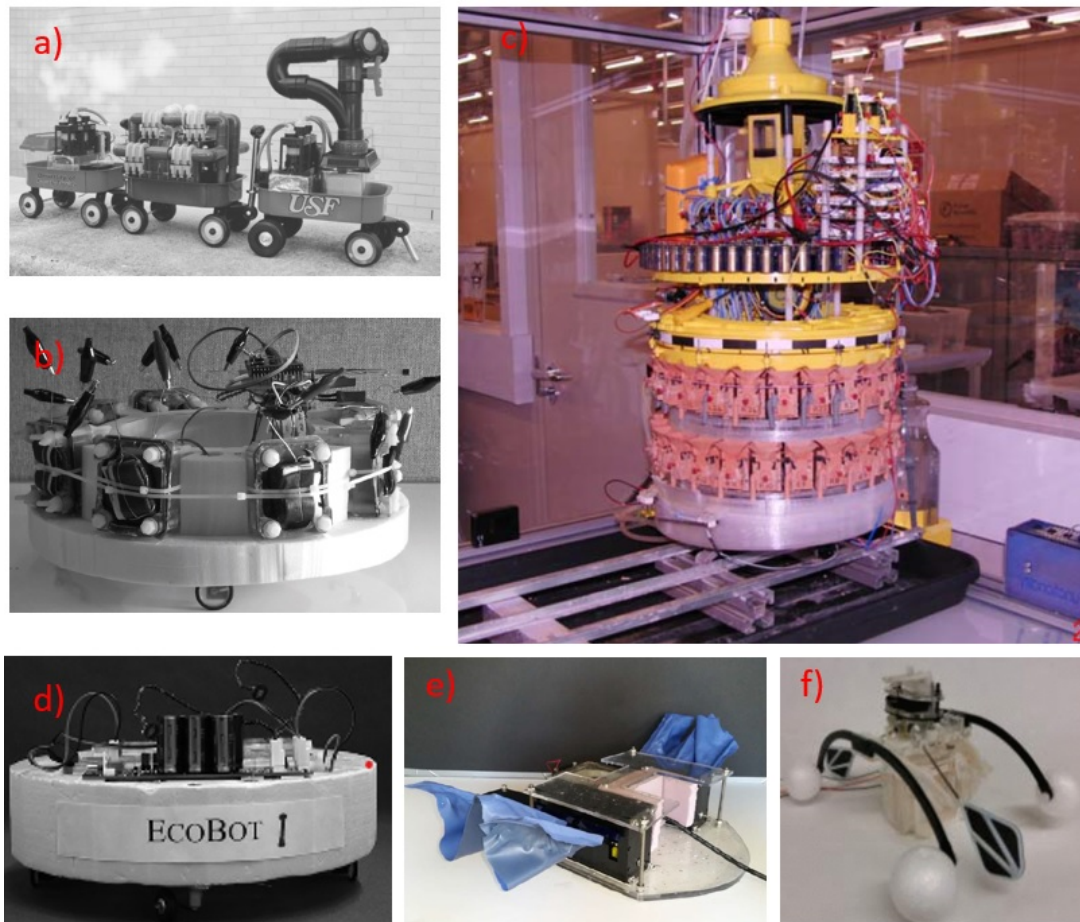


Figure 2. Previously constructed gastrobots. a) "gastronome" [6] - train-robot powered by microbial fuel cell (MFC) b) EcoBot-II [7] c) EcoBot-III [8] in its testing environment d) EcoBot-I [9] e) Marine gastrobot [10] f) Row-Bot [11] - marine gastrobot.

2. Needing, Liking, and Wanting in Human

Human tastes and food preferences are extremely complicated and give rise to the enormous amount of dishes, and multiple recipes for each dish. Even though there is a huge interest in this area by researchers and the food industry, one, simple model of human preferences does not exist. We attempt to describe these preferences by combining together three basic drives that influence human feeding behaviour - needing, liking and wanting.

2.1. Need

The human body has a large variety of needs that must be filled to maintain homeostasis. These needs usually fall into three major categories: energy, macro- and micronutrients. These needs are objective, anchored in the physical world, constrained and directed by both evolution and learning processes to produce unique personal preferences. Finding an exact required amount of these nutrients is not feasible, but most countries have recommendations (eg. [13], [14]), varying with the age, gender and physical activity of the consumer. The real requirements may vary from recommendations, with some extreme outliers documented. For example, Kenyan runners when training spent 3600 kcal/day while consuming 3100 kcal/day, compared to the 2500 kcal/day recommendation for their age group [15]. Micronutrients also need to be supplied in adequate



Figure 3. Challenges for constructing gastrobots - robots powered by biomass or food.

quantity, with deficiencies resulting in decreases in intellectual function [16], bone density, and other illnesses[17].

Failing to fulfil some needs causes sensations of discomfort (such as hunger, and thirst) which motivate action. On the other hand, failing to fulfil other needs may not result in any symptoms in the short term, or may cause generic symptoms that do not motivate consumption of the specifically needed foods. For example, vitamin B12 deficiency causes symptoms ranging from the sourness of the tongue and tiredness to low blood pressure and psychosis[18] - non of them prompting consumption of B12-rich foods like meat or eggs[19].

Overall, some needs cause a strong motivation to consume specific foods to reduce the drive state, while others do not. Interestingly, in some cases like hunger, it motivates to start consumption, but fulfilling the need does not entirely motivate stopping the consumption[20]. Therefore, there is clearly a space for additional mechanisms beyond physical needs that dictate the quantity of food consumed.

Taking all of these considerations we model Needs as a physical constraint for taste. These are immune to most of the external and contextual factors such as social pressure, specific available foods, or ideology. We consider Needs as a reliable input that plays a part in learning what we like and acts as an input to decisions as to what we want.

2.2. Like

Liking is a long-term estimation of the value of food. In humans, it comes both with innate components and learning. For example, sweetness, usually measured by sucrose concentration, is pleasant for all ages[22], with signs of hedonistic pleasure present even in newborn infants[23].

Basic Taste	Innate Response	Development Time
Sweet	Positive	In Utero
Sour	Negative	In Utero
Salty	Positive	4-6 Months Old
Bitter	Negative	In Utero + Maturation
Umami	Context-Dependent	Unknown

Table 1. Innate human response to basic tastes according to [21].

Regardless of this innate proclivity for sweetness, preferred concentrations change with age, with older people finding high sucrose concentrations less pleasant[24]. With specific foods, children tend to refuse the intake of new foods/flavours and need to taste them as much as 10 to 15 times before they will habituate and find their taste pleasant[25]. A good review of the development of innate proclivities to basic tastes is given in [21], which we summarize in Table 2.2.

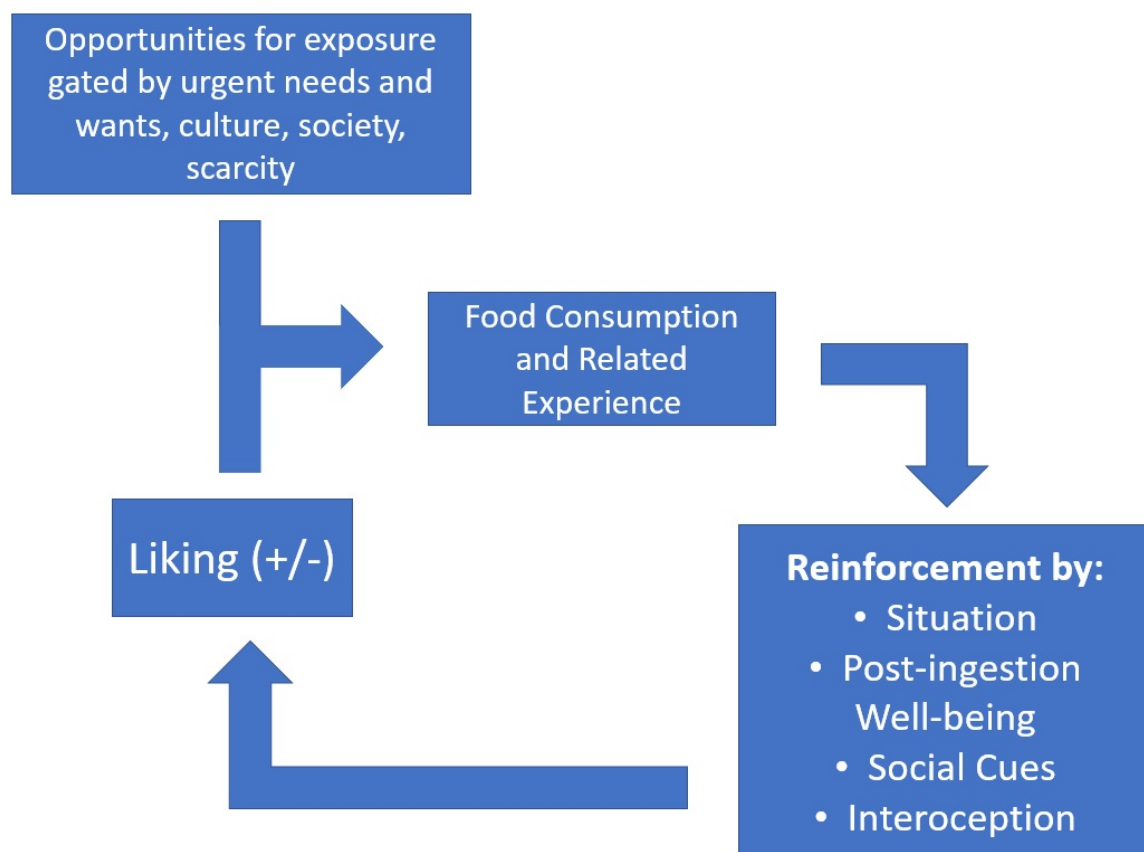


Figure 4. Model of "learning to like" as suggested by [21].

Liking is a learning process, starting with certain biases which are adapted and changed over time. Interestingly the reward is not only fulfilment of the body's need, but can also come from external conditioning with social or physical stimuli. For example, people repetitively presented with a certain kind of tea with sugar learn to like it more[26]. An example of social conditioning is food aversions passed down in families[27]. Therefore, liking can be understood as a slow,

long-term oriented learning process holding a time-independent and context-independent value of certain foods. Importantly, as with any learning, it is biased by the data it learns. It is effectively closed in a control loop as shown in Figure 4. We will discuss this loop in the next section.

2.3. *Want*

The literature review above showed that, while there are some imprinted preferences for taste, these are quite general, and fluid. There is no general, objective measure of taste, yet it's immensely important for survival. We have seen that while the only physical anchor comes from bodily needs, that (for most) are rather easy to fill in the developed world[28], [29], we are still motivated to eat specific things, and this section is a discussion of how it happens in humans.

One of the most interesting aspects of the "Want" element of taste is how we come to be motivated to try new foods: As has been discussed, humans prefer known tastes. However, taste is not the only perceptual modality that can produce a sense of familiarity. For example, children tend to prefer to try the fruits that they have seen before, even if they have never eaten it before[25].

This cultivated liking through non-gustatory familiarity can be gained by via exposure to advertisements. Repeated presentation of recognisable foods and brands motivates buying and eating certain foods. Beyond this, analysis of advertisements placed in magazines[30] provides statistics on claims used for both hedonic and functional foods. Overall, properties like nutrition, taste, novelty, lack of (negatively perceived) substances, and general positive effects on health are emphasized. This speaks to the large variety of considerations that motivate specific consumption decisions, beyond simply hedonic enjoyment and bodily needs.

Finally, dietary decisions are also dependent on the environment. For example, the sugar levy in the UK reduced soft drink consumption by 18%[31]. The study also showed that 80% of reduced calorie consumption came from producers lowering the amount of sugar, possibly leading to more exposure to drinks with less sugar. Moreover, large portion sizes motivate individuals to consume more of the presented food regardless of individual needs and desires[20]. Even social environment can greatly change if and how much we eat[32]: For example, an individual who has not eaten for 24 hours (and thus has high Need) will still reduce their consumption to better match a social eating partner who has not been similarly deprived[33]. The identity of those who influence eating habits also matters. Family members and friends have more effect than coworkers, while coworkers have more effect than strangers[32]. The exact effect of social pressure depends also on the pressured person. For example, males consume much more snacks when in a group with friends in comparison to a group of strangers, while this effect is not present for females. On the other hand, when paired with strangers, females tend to consume less than those paired with a friend, an effect that is not present in men[34].

Overall, the "wanting" part of the system can be considered as the motivator of specific individual consumption events. It can be understood as an estimation of expected value, not only based on intrinsic properties (.e.g nutrients) or time-invariant value, but also specific context.

3. MFC Powered Robot's Needs

The literature describes some instances of feeding in gastrobots, but the procedure was hard-coded and did not include tasting the food. For example, Ecobot-III[8] was tested in a highly structured, robot-friendly arena, where the Ecobot was always fed the same food, in the same quantity and in the same place. In this setup no adaptive decision-making was required for the robot, therefore did not require any tasting ability to pick the correct food. Regardless of this shortcoming, the robot still had needs, that needed to be fulfilled for the robot to function. And from the need, liking and wanting could also emerge in the right environment. Therefore, in this section, we analyze the hypothetical needs of an MFC-powered robot.

Measured Quantity	Proposed Sensor	Equivalent in Human
Chemical Oxygen Demand or Dissolved Biomass	Camera (Color, Transparency)	Caloric Value
pH	H+ Sensitive Electrode	Sourness
Na+ Ions	Na+ Sensitive Electrode	Saltiness
P, N Ions	Ion Sensitive Electrodes	Micronutrients

Table 2. List of sensors proposed for the robotic taste.

3.1. MFC's Need

A robot's needs are usually specified as energy consumption or maintenance schedule. In the case of gastrobots, the needs become more complicated, to a point where a perfect diet is being discussed[35], and possible sources of sustenance in various environments are being explored. It is theorized that a carnivorous diet is preferred, as meat offers higher calorie density than plant-based foods[35]. While we will limit the environmental complexity in this discussion, the caloric density of the food is crucial, as the fuel cell can be loaded only so many times in a period of time, and higher organic matter density produces more power[36].

Moreover, the MFC needs a specific environment to facilitate the growth of the bacteria. It requires specific substances which are not a source of energy, reminiscent of the role of micronutrients in the previous discussion, and particularly their role in maintaining the microbiome. For example, salinity inside the MFC has a huge effect on power production, with a solid peak at 1% of salinity, but falling down to zero at salinity of 2%[37]. Similarly, acidity is also a big factor as the bacteria grow best in pH around 7[38]. Other ions will also influence the power generated: Higher ionic load would usually increase generation[39]. The adequate temperature of food is required as it also influences power production[40], an effect well documented due to the seasonality of power production in sewage treatment plants[41].

The last need we discuss is the need to prevent fouling of the MFC membrane. Fouling is a process of growth of microorganisms on the membrane or accumulation of other substances that limit the membrane's permittivity. Fouling shortens the life of MFC[42] and is one of the likely factors that can cause the shutdown of the robot. One of the factors that increase fouling is over-feeding[43]. In such a case extracellular polymeric substances(EPS) build up on the cell membrane. Excess nitrogen and phosphorus concentration also contribute to accelerated fouling of the membrane[44].

4. Robot and Environment Design

As we are focusing only on a few of the challenges for gastrobots the environment will be very specific in some areas, while very basic in others. Moreover, due to the focus on taste, we keep most of the robot and environment design the same as in the case of Eco-BotIII[8]. All the adaptations that we would introduce for the sake of the thought experiment are listed in this section.

4.1. Taste Sensing

Robotic taste is a recent development[4], [45], and has so far been used to cook dishes catering to specific human preferences. In this case, we choose a combination of sensors that can sense the substances needed by the fuel cell. Moreover, this array of sensors must be able to sense substances that humans taste. It is crucial, as the aim of the theorized system is to serve as a sense of taste for a robotic chef in the future.

Starting with the measurement of biomass concentration in the feed is crucial. Usually,

it is estimated by measurement of Chemical Oxygen Demand(COD) in a sample, which is traditionally measured by incubating it in a warm environment. Currently, more compact sensors are available for COD measurement[46], and COD measurements on a large scale are possible[47]. However, COD can also be estimated using factors such as the colour or transparency of the sample. This is the solution we propose for our setup, as the robot can simply learn to like samples of specific colours. Saltiness, as well as the concentration of each ion that was found critical, can be measured by ion-sensitive electrodes. This includes the measurement of pH. Overall ionic strength should also be measured[48]. A conductance sensor is also a good candidate for this task. The recommended sensors and their relation to human taste are summarised in Table 2.2. The use of biosensors for specific substances is also an option but not recommended here due to their inability to work in a messy food environment.

4.2. Feeding Mechanism

Feeding mechanisms for gastrobots are not well researched. There was a successful attempt to build a robot that hunted slugs[49]. Moreover, it was shown that mastication can improve taste sensing for robots[45]. Given the scarcity of data, we do not attempt a complicated feeding mechanism for our hypothetical robot but will use liquid feeds only. The robot will, after using its sensors on presented samples, decide which sample and how much it should consume by pumping it inside its MFC, while evacuating ('spitting out') unwanted or excess liquid.

4.3. Energy Storage

Due to the nature of MFC the energy production is slow and the delivered voltage is dynamic and unpredictable. These characteristics make usage of switching DCDC converters problematic, and the output of charge pumps inconsistent. Therefore, we find that using a capacitor battery is the best approach because it is very flexible as comes to power sources. Moreover, based on previous experiments done on Ecobot-III[8] platform, we notice that the practical voltage of the capacitor is varied inside a rather small range. Therefore, we think that measuring the current output of the MFC is a sufficient measure of generated power. Moreover, the MFC current(I_{MFC}) measurement can be done indirectly by measurement of capacitor battery voltage(V_{cap}), as these two values are tied by capacitor equation:

$$V_{cap} = \frac{1}{C} \int_t I_{MFC} dt$$

, where C is the capacitance of the battery. This eliminates the need for direct current measurement.

5. Need, Like, Want - Artificial Intelligence

5.1. Need

While needs are grounded by the MFC's needs, they must be represented for the machine learning of taste, which will be specified in the next section. For now, we assume that the MFC cell has an extensive set of sensors inside the MFC, that collect information about the internal state. We require a way of translating these measurements into signals that can be read by neural networks and explain well the current need for the MFC. Moreover, the context of these sensors, or the values they measure is not known outside of this part of the system as it represents the physical needs only. We propose two possible approaches to this problem.

The first approach is data-driven and is based on an exhaustive search of all possible combinations of nutrients inside the cell. The resulting generated power and resulting fouling of MFC's membrane would be recorded on a scale, and become the need satisfaction value. This function can be used to find the most urgent need just by computing a gradient, and this

information could be the output of the block representing needs. This solution, while elegant and with analogical concepts in machine learning, is nonetheless hard to implement. Firstly, each of the parameters specifying the composition of the feed would need to be quantized with the relevant resolution, but a higher resolution would require more experiments as the MFC need to be physically tested for every parameter value separately. Moreover, the system would have at least one parameter for every "taste" sensor, making the number of experiments grow further. If we use n parameters to describe the needs, and each of them was allowed m values, the number of required experiments e is specified by the following equation:

$$e = m^n$$

, making the experimentation not feasible. Regression is an approach that could help to reduce the number of experiments needed by filling the gaps between the parameters. However, the cost of it is adding another layer of learning to the system. Moreover, this learning would be applied to the part of the system that specifies needs, and this part of the system that provides a grounding to physical constraints. Therefore, we decide that this approach is not feasible due to a possible reality gap.

The other approach is to hard code the known needs for the MFC, making use of experiments already within the literature. This approach comes with numerous advantages. Firstly, the best-performing mixtures of feed are well-studied and can be expressed as an equation. Moreover, the system becomes more explainable and well-grounded to the physical requirement of the cell. One possible critique of this approach could be based on the fact that we can program only the things that were reported on in the literature. We still find it the best solution. Moreover, this solution is very similar to the human body where sensing and perception are very limited too. This means that not all needs are signalled by the body and not all nutrients can be sensed in the food. In this place, it should be noted that the same situation happens in the human body. Effectively, this approach would output binary signals corresponding to each of the parameters known to change the energy generation from MFC, 0 when the value is in range and 1 when the value is outside of the safe range. For the sake of this argument we choose to follow with hard coding known MFC needs as they are well known, and do not bring additional layers to the discussion.

5.2. Like

Liking is a long-term integration of the value of consumed food. This value is malleable, subject to change over the course of a lifetime, but stable on a day-to-day timescale. Therefore, the learning rate of this part of the system should be low, regardless of the actual implementation. We also want a system that takes into account all advantages and disadvantages of consuming a particular food, not only nutritional ones. Moreover, in this case, perception of food is limited, so liking is realistically a learned assignment of value to experienced taste. It can be considered as a black box that returns the expected value of consuming the food currently tasted.

To get as broad a take on these needs as possible, we propose to measure the value of particular food by integrating the generated current over a time window after consumption $t_{digestion}$. $t_{digestion}$ is itself a parameter of the model and should be set accordingly to the throughput of the food in MFC. The value V of a given taste, masked as a vector T , can be then computed with the following equation:

$$V = \int_{t_0}^{t_0+t_{digestion}} I_{MFC} dt$$

, where I_{MFC} is current generated by MFC, and t_0 is consumption time. These values will always be used to update the liking model after the digestion time has elapsed.

The next step is to find a generalization of previously obtained values to all possible tastes that can be encountered, without the need to experience all of them. Therefore, multivariate regression is necessary. The multivariate regression model is of the following form:

$$y \sim f(X, B)$$

where y is the estimated function, X is a set of variables, and B is a set of adjustable parameters. This is the broadest form of multivariate regression, and in our case, the estimated function in food value V . This estimation is done base on the tasting sensors values X . Therefore, for our robot X becomes:

$$X = \{COD, pH, saltiness, [P], [N]\}$$

, where $[N]$ denotes the concentration of nitrogen ions. Finally, we need to specify B , and for this, we need to agree on how to model function V to find parameters B . This is a problem with many possible solutions, but the chosen solution must make a model that represents physical reality well. We start with making the following observations:

- All the measured values have an optimum.
- A plateau around optimum is preset, and the current generated steeply falls off away from the optimum.
- Not meeting just one condition is enough to hamper power generation.

Taking these facts into account, we consider a sum of quadratic functions. Each of these can be specific to one of the measurements only. The whole V function will be then estimated as:

$$y \sim b_0 + b_1 * COD + b_2 * COD^2 + ... + b_{n-1} * [N] + b_n * [N]^2$$

where parameters b_1 through b_n need to be found by regression. Assuming this form of regression is somewhat arbitrary and likely not the most optimal, but it mirrors the natural experience of liking in humans, where some of its aspects are innate.

5.3. Want

Wanting is the final system that decides the action. It takes into consideration the unmet physical needs, palatability of the food and external signals. Working in our example of three foods presented it should produce a signal specifying how much should be ingested from each of the foods. Therefore, a fully connected neural network with three output neurons is preferable. An example network with two hidden layers is shown in Figure 5. MFC's immediate needs are signalled by input neurons n_1 through n_n , that signal a binary value 1 or 0. The taste assessment of each of three presented foods is signalled by inputs l_1 through l_3 , which take an analogue value between 0 and 1. Finally, any number of inputs c_1 to c_n can be used as a description of the context around the robot. A relatively high learning rate should be used for this network to allow quick adjustment to the changes in the environment.

6. Aligning Robot and Human Taste - Acquired Taste

As discussed before, acquired taste is commonly found among humans, in various societies. Due to the robot's taste similarity to human taste, it is also possible to acquire a taste based on external or "social" cues. We simulate these "cues" as external energy injection, that is indistinguishable for our algorithms from energy produced by digestion. As discussed in Section 4.3 we use generated current as a measure of gratification, therefore this injection will be in the form of current, by the circuitry shown in Figure 6. This is effectively an extra, not nutritional benefit of consuming a certain food. These injections can be both positive and negative, similar to social cues in human society.

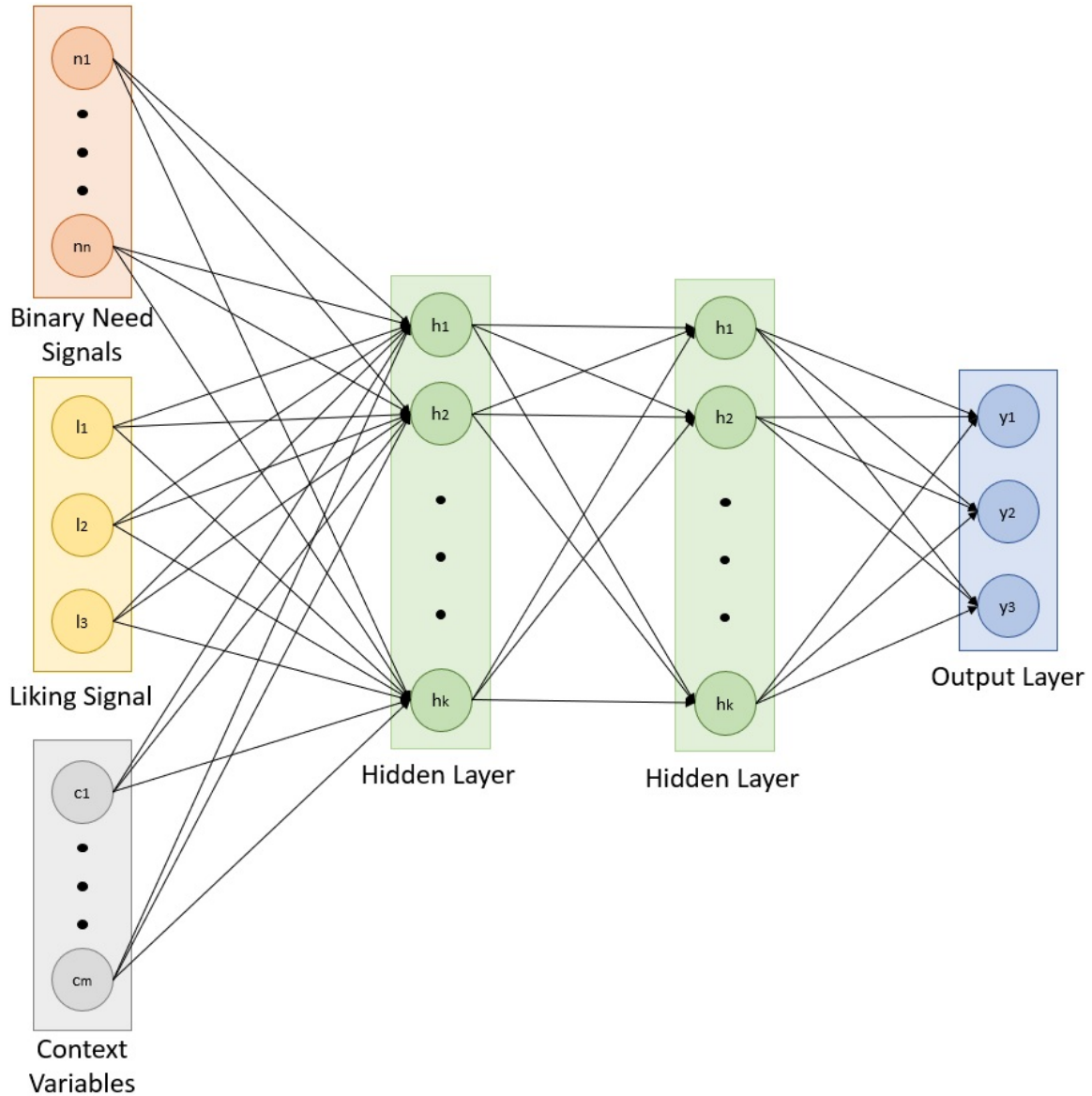


Figure 5. Design of a neural network that simulates human wanting process. It uses signals of liking the taste, nutritional needs and information about the context of the meal. Three output neurons decide which of the three presented feeds to ingest.

6.1. Acquired Taste Teaching

The teaching of the acquired taste would be done by producing a chosen food and presenting it to the robot. When the robot ingests the given food we start injecting an extra current into the system for the time $t_{digestion}$, discussed in the previous section. This should cause an increase in liking of this specific food, and also liking of all other foods ingested together with the target food. Moreover, all other foods ingested more recently than t_{digest} before the ingestion of the externally favoured food will be partially favoured too. Therefore, the learning will be not clear cut, just as in humans, but with enough food presented to the robot, it should result in liking the preferred food more than its nutritional value suggests.

We would also like to suggest the most likely way to use this way of learning the taste. The power generation from MFC is not likely to be enough to power a robot that has enough

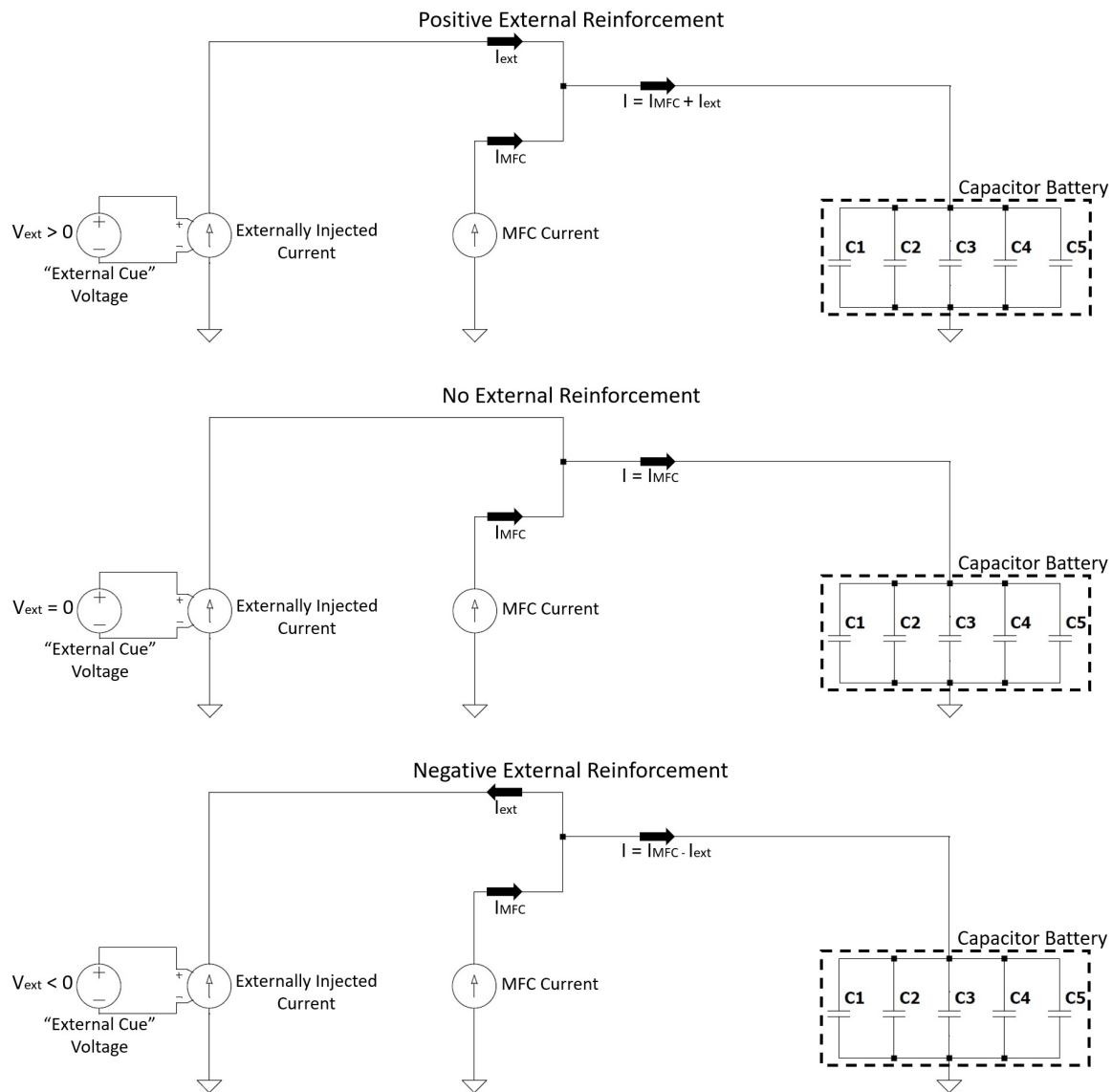


Figure 6. Figure showing microbial fuel cell with a parallel current source, which simulates non-nutritional cues, and therefore makes some foods valued more than their nutritional value.

dexterity, carrying capacity, and speed to become a robotic chef. Therefore, we would suggest operating the proposed system as an auxiliary device until the MFC technology progresses. The system can effectively act as an external controller of a robotic chef, where the MFC provides a symbol grounding for the taste AI.

7. Discussion and Conclusions

This chapter has discussed the previous experiments with robots that power themselves by ingesting organic matter - gastrobots. While this technology was initially thought of as a way to make robots independent of batteries or charging points to operate them in long deployments, this chapter proposes to repurpose this technology as a way of solving the grounding problem for robotic taste by binding the taste to the physical survival of the robot.

The proposed binding is inspired by the natural way this binding is done by humans, that is by

mechanisms of needing, liking and wanting. Needing covers the short-term critical requirements, liking is the integration of benefits that exact food brought over the lifetime and wanting brings the situational context. In a robot the needs should be hardcoded bounds on the chemical composition of MFC, liking is the integration of produced current and wanting should be learned based on the previous outputs and the state of the environment.

The chapter also shows how current injection can simulate non-nutrition rewards and punishments for the robot, enabling it to simulate things like peer and social pressure by current injection. It is also proposed to use MFC simply as a way to ground taste learning for robotic chefs by using it as an auxiliary device rather than the main source of power.

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