

# Toward Metabolic Robotics: Insights from Modeling Embodied Cognition in a Biomechatronic Symbiont<sup>1</sup>

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**Abstract** We present a novel example of a biomechatronic hybrid system. The living component of the system, embedded within microbial fuel cells, relies on the availability of food and water in order to produce electrical energy. The latter is essential to the operations of the mechatronic component, responsible for finding and collecting food and water, and for the execution of work. In simulation, we explore the behavioral and cognitive consequences of this symbiotic relation. In particular we highlight the importance of the integration of sensorimotor and metabolic signals within an evolutionary perspective, in order to create sound cognitive *living technology*.

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## Keywords

Embodiment, living technology, microbial fuel cell, energy management, artificial metabolism, motivation, cognitive systems

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## I Introduction: Control, Cognition, Life, and Affect

In recent years, robotics has redirected much of its traditional emphasis on precision, speed, and controllability toward a new set of objectives. Future robots are expected to prove robust, adaptive, and autonomous. They should learn from their experience and possibly self-repair, self-reproduce, and evolve to become more adapted to their current environment [3, 39].

Indeed, the operative scenario for future robots has been drastically redrawn and made more complex. After mastering the protected environment within the high-tech factory, the challenge for the robot to come is the world in its least structured form. Novel open-ended tasks include, for example, autonomous exploration of inhospitable and unexplored territories, participation in search and rescue actions, and coping with social dynamics in robot-robot and human-robot interactions. The uncertain (sometimes the unknown) described by limited, inconsistent, and unreliable information, characterizes a significant part of these activities. The environment demands contingent adaptation to temporal and spatial features and, at the same time, underdetermines the appropriate robot behavior. The environmental intrinsic dynamics express an inertia that the robot often has

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no power to influence directly (e.g., this is the case of a marine tidal stream for a small robotic explorer, or a hostile and non-collaborative human interlocutor for a service robot). The robot has to adapt by synchronizing to exogenous dynamics, thus operating under time pressure. Furthermore, an autonomous robot is expected to manage and provide for its own energy needs by finding in its surroundings the resources necessary to its *energy autonomy* [29], while operating under limited or no human intervention.

In its initial formulation, the problem of robot control has been mapped neatly onto the traditional domain of engineering methods. On the other hand, coping with the new class of scenarios seems to urge a novel set of techniques. Growing attention has moved toward the one system that, to our current knowledge, masters the new objectives of robot control: the (biological) mind, as an invaluable source of inspiration.

This search is compelling. Indeed, the scientific community has good reasons for a basic intellectual interest in the study of the mind. Nevertheless, there is even more on the plate for the pragmatically oriented. While robots are currently perceived as ideal candidates for the next electronic revolution (e.g., [16]), mastering the implementation of even relatively simple levels of “intelligence” would not simply boost the performance of current artifacts. It would rather launch a broad technological revolution. Problems like the actuation and control of still-functional muscle groups or exoskeletal frames for paraplegic individuals (e.g., [19]) or the creation of genuinely autonomous robotic systems displaying flexible behavior and some level of empathy with their human users could be approached on more solid grounds.

However, science lacks a satisfactory *theory of the mind*. To date, this can be reasonably regarded as a fact. Currently, science is still struggling to find the correct perspective and set of methods to fill this gap. In parallel, a critical rethinking of the general organization of cognitive systems has rediscovered a more systemic view of the mind. The classical brain chauvinism in the description of cognitive processes is undergoing deep reevaluation, and an embodied cognitive science—that is, a cognitive science where the body plays a foundational cognitive role—has emerged quite naturally within this more systemic view of the mind [10, 12, 45, 52]. The body of the cognitive agent is not simply a passive framework that relocates in space and time the agent’s interface with its world. The body actively redefines the cognitive problem by processing information [11, 38]. The mind emerges from the causal interweaving of coupled body, brain, and environment [6]. Increasingly, embodied cognitive science inspires current cognitive robotics [38].

To date, though, the role of the body in cognition has mostly been studied in terms of dynamics that take place along the surface dimension of the body (e.g., see [12, 38]). The core of this article explores a very specific research track that has recently emerged within cognitive science. Recent work has revitalized William James’s classical somatic theory of emotions [23] in the light of neuroscientific evidence [13, 14]. According to Damasio, a hierarchy of bodily processes (metabolic regulation, basic reflexes, immune responses, pain and pleasure behaviors, drives, and motivations), triggered by emotionally relevant stimuli, determines the substrate for emotion proper. Emotional dynamics can be interpreted as sophisticated strategies for the survival of the organism, “viscerally” rooted in the inner bodily mechanisms [13, 14, 23, 26]. Under different emotionally relevant stimuli, the body prepares for action and participates in the cognitive act. In the experimental work reported in this article, we will address this kind of emotional dynamics in a rather loose sense, therefore referring to the broader term “affect” to describe them.

These ideas are highly relevant to robotics. Which level (if any) of biological detail should we impose on biomimetic modeling in order to achieve useful cognitive properties that characterize living systems? Some authors argue that the complex system of bodily processes might be a crucial key to a general understanding of biological cognition and a powerful organizational principle for the design of robots with extended capacity for adaptivity and autonomy [36, 37, 58, 59]. Obviously, this approach fully discloses the problem of the connection between life and mind and opens questions on which kind of (artificial or natural) systems are suitable for the study of the mind [4].

More than six decades ago, a pioneering group of British cyberneticists ventured on a path that seems particularly relevant under this perspective. Still today, their achievements deserve our full

consideration. With his minimalist robotic models, *machina speculatrix* and its evolution *machina docilis*, Walter [53–55] drew attention to the emergence of the mind as a complex dynamic interaction of brain, body, and environment. His robotic tortoises were designed to be sensitive to specific interactions (e.g., environmental light distribution and mechanical contacts with objects). Their actual behavior was causally determined by the fields of force that owe to the interplay between the environment and the machine itself. The metaphor of mind that is brought forth by the model is one of dynamic interaction between two interacting systems: the environment and the machine endowed with an extremely simplified control system. The environment was explicitly considered part of the feedback loop [55].

Ashby [1] implemented an elegant electromechanical stylization as his model of a mind, the *homeostat*. Ashby's homeostat extended the image of a brain continuously engaged in a dynamical interaction with its environment by integrating the means for a continuous adaptation to new and unexpected challenges. Within a cognitive system, he defined as *essential variables* (EVs) a subset of the organism's variables that are critical to its viability (e.g., blood pressure, heart rate, blood concentrations of hemoglobin and glucose). The species-dependent specificity of these variables and of the range admitted for them takes the idea of embodiment, applied to Ashby's thought, to rather extreme consequences. The relation between different EVs and lethality is species specific and nonuniform within the same species.

According to Ashby [1], *adaptation* has to do with the maintenance of all EVs within physiologically viable limits. In the homeostat, an event that pulls one or more EVs out of their physiological range will indirectly trigger a sequence of random structural changes in the phase space of the system. The sequence will be sustained until a new condition, where the dynamics of all EVs are maintained within their limits, is reached. Wiener [56, p. 38], remarking on Ashby's idea of an “unpurposeful random mechanism which seeks for its own purpose through a process of learning,” celebrated Ashby's model as “one of the great philosophical contributions of the present day.” In the analysis by Pickering [40], Walter and Ashby bring forth the ontological view of a performative (and radically nonrepresentational) biological brain, being designed by natural evolution to produce effective action in its environment.

Despite the fact that mainstream artificial intelligence has deployed a view of the mind based on symbolic representations, several lines of research have renovated the original cybernetic intuition. Neurophysiologists and cognitive scientists have shown that the methods of dynamic system theory can be effectively applied to interpret and model biological cognition (e.g., [24, 46, 49]). The dynamic system approach to cognitive science has been explored at the theoretical level [5, 10, 50]. Cognitive tasks of minimal<sup>2</sup> cognitive relevance have been synthesized and analyzed as robotic models [7, 22, 35].

In the remainder of this article we will present an original and novel robotic prototype, a bio-mechatronic hybrid endowed with a simple artificial metabolic system. An on-board living bacterial population processes biomass, providing the robot with the electrical energy needed for sensing and action. The analysis of computer simulations will allow us to predict the crucial properties that are likely to emerge from such a system at different stages of its technological development, namely, in short-, medium-, and long-term perspective. The final discussion will highlight the cognitive implications that might be relevant to the development of a sound cognitive *living technology*, that is, engineered systems whose power specifically derives from core properties of the living system [4].

## 2 A Robot with a Living Core

Over the last decade, researchers at the Bristol Robotics Laboratory have been working on the development of a peculiar family of prototype robots, EcoBot [21, 30]. Its source of power depends entirely on the availability of water and biodegradable mass. In fact the energy that is supplied for

<sup>2</sup> Analogously to the case of early cybernetic models, the usual inherent simplicity of these cognitive models should be interpreted at the same level of idealization that is proper to frictionless planes, leakless capacitors, perfect gases, and massless springs [1].

the robot's sensing, actuation, and control derives from a robotic variation of the *microbial fuel cell* (hereafter MFC) technology.

## 2.1 Oxygen-Diffusion Cathode Microbial Fuel Cells

In the anodic compartment of a MFC, an anodophilic population of bacteria in tight adhesion with the anodic electrode builds up an electrical potential difference by oxidizing the biomass contained in a liquid substrate (Figure 1). In MFCs that do not make use of exogenous consumables, the electron transfer from the bacterial intracellular space to the anodic electrode can take place via endogenously produced mediators, direct membrane-electrode contact, or nanowires [27, 41]. The anodic bacterial population, as long as it is provided with fresh substrate to maintain a well-buffered and healthy environment, tends to reach a stationary yet metabolically active growth dynamic. The substrate can be fed by refined renewable biomass (e.g., sucrose, acetate, starch), but also by unrefined biomass (e.g., rotten fruit, flies, green plants, urine, and wastewater) [30].

A semipermeable membrane separates anolyte and catholyte, at the same time preventing any flux of  $O_2$  to the anode and allowing the migration of  $H^+$ , a byproduct of oxidation in the anodic compartment, to the cathode. Since the robot prototype is intended to be an autonomous system, the (more efficient) exhaustible chemical-electrolyte-based cathodes, traditionally used in MFC research, have been replaced by oxygen-diffusion cathodes, partly open to the external atmosphere and, for the remaining part, filled with water. This choice translates into a self-sustained electrochemical process. Hereafter, we will specifically refer to this configuration, known as the *oxygen-diffusion cathode microbial cell* (ODC-MFC). In an ODC-MFC (Figure 1),  $H^+$  ions reduce at the cathode

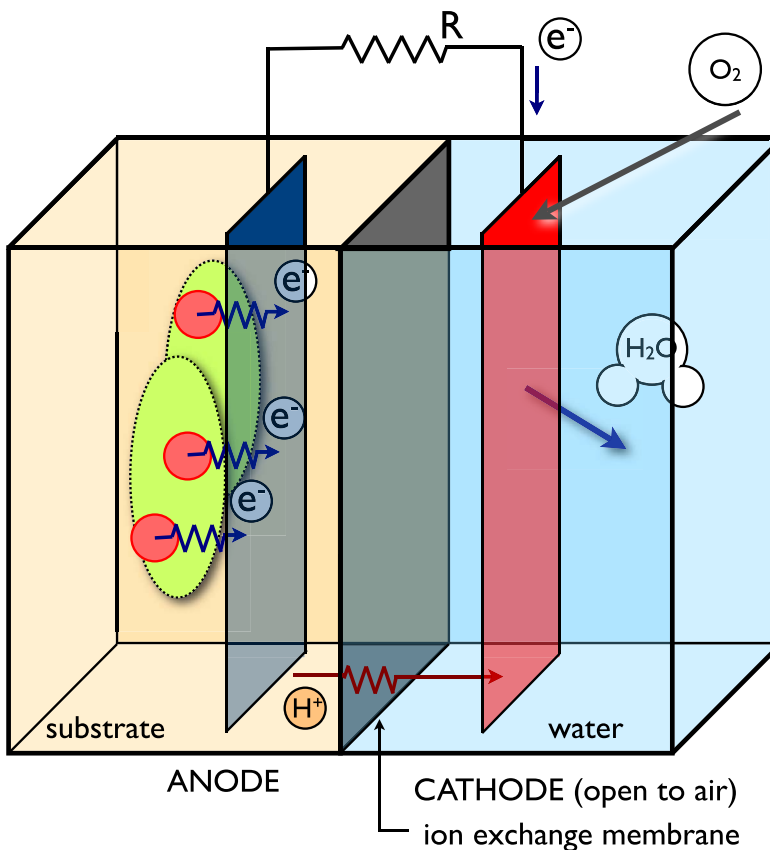


Figure 1. Schematic of an oxygen-diffusion cathode MFC.

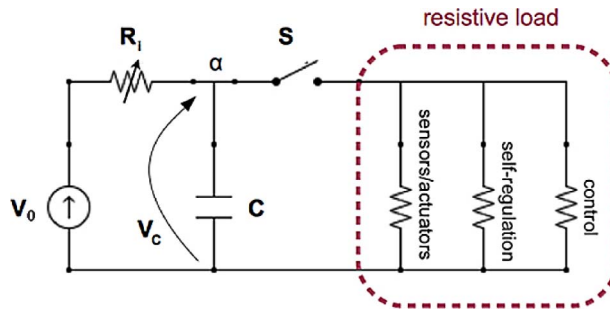


Figure 2. Model of ODC-MFC energy generation. The lumped parameters  $V_0$ ,  $R_i$ , and  $C$  schematically represent our platform-independent model. A dashed rectangle represents the robot as a resistive load.

by combining with  $O_2$  and accepting electrons to endogenously produce a little water (normally insufficient to compensate for the loss due to evaporation), thus closing the electric circuit. The presence of a continuous flow of highly oxygenated water supports the cathodic chemical dynamics, promoting optimal efficiency. Nevertheless, this is not an option for autonomous terrestrial robots. Accordingly, the amount of water present in the cathode and of the chemical-bond energy in the substrate are the two crucial parameters for the system.

## 2.2 A Mathematical Model of the ODC-MFC

We developed a mathematical model of the ODC-MFC [32]. Differently from other models of MFC available in the scientific literature, its high level of abstraction omits the details of the physical-chemical level. Thus our model allows its use as a platform-independent plug-in that can be easily integrated within standard computer robot simulations, with extremely limited computational overhead.

We developed a simple resistance-capacitance electric model (Figure 2). Both the electromotive force ( $V_0$ ) and the internal resistance ( $R_i$ ) of the ODC-MFC depend on the level of hydration at the cathode and on the chemical energy in the substrate. The functional relations for these crucial parameters were identified by using energy generation data extracted from the physical ODC-MFC-powered robot prototype [32]. An external capacitance ( $C$ ) transiently stores the available energy. Its presence is a design choice, due to the electrical constraints imposed by the physical sensors and actuators for robotic applications. A hysteresis cycle ensures that the tension supplied to the robot (the resistive load in Figure 2) remains within a reasonable range. When the tension across the capacitor exceeds a given upper threshold, then switch  $S$  in Figure 2 closes and the accumulated energy is distributed to the load (e.g., to the robot). When a lower threshold is reached, then switch  $S$  opens and such distribution is inhibited while the capacitor recharges. The relations that mathematically describe the system parameters ( $V_0$  and  $R_i$ ) and their physical interactions constitute the platform-independent model of energy generation. On the other hand, the distribution of the available energy must be estimated on the basis of the actual robot in use.

For the reader's convenience, the equations of the model are reported in the Appendix. A more detailed description of the model is available from Montebelli et al. [32]. What is important for the current discussion is that the model produces realistic ODC-MFC energy generation dynamics. The levels of cathodic hydration and chemical energy in the anodic substrate determine the instant rate of energy (power) that is generated by the ODC-MFC. In other words, well-hydrated and well-fed robots recharge faster and therefore have more energy for their actuation. Observe that both the hydration level and the chemical energy in the substrate are subject to temporal decay. This models the spontaneous evaporation from the cathode and (undesired) biochemical processes that degrade the substrate in the digester.

In simulation, sources of water and food can be easily provided by the environment, and the desired modality of interaction between them and the robot (ranging from more realistic to heavily

abstract) can be implemented. Indeed, the implementation of mechanisms to directly access the environmental resources (i.e., collecting water and biomass for its digester), although not yet implemented, is possible for the physical robot prototype as well.

### 3 Simulating the ODC-MFC-Powered Robots of Today, Tomorrow, and Beyond

As already mentioned, by using the ODC-MFC model we can readily anticipate the developments of the MFC technology for robotic applications, while maintaining realistic energy generation dynamics. Free from physical limitations, the number of on-board ODC-MFCs can be extended as desired in arbitrary stack configurations.

We can conceive of the ODC-MFC-powered robot as a biomechatronic symbiont, where the two hybrid components not only benefit from each other, but depend on each other for their own survival [30]. By processing biomass, the living component in the anodic compartment produces electrical energy that is distributed to the mechatronic component. In return, the latter provides sensorimotor facilities that are essential to collect food and water that keep the bacterial population alive. To date, the power density produced by MFCs in general, and even more so by ODC-MFCs, is admittedly extremely low. Nevertheless, this technology has been proved sufficient to substantially support the energy demands of important applications, such as wastewater treatment and mobile robot platforms [21, 30, 57].

#### 3.1 State-of-the-Art ODC-MFCs

Current physical ODC-MFC-powered robots display minimal behavioral dynamics. Different generations of EcoBot can be scaled up from 8 to the current 48 on-board ODC-MFCs. Each ODC-MFC provides around 0.1 mW to its load at about 0.2 V. The energy demand for the actuation of a robot like EcoBotIII should not be overlooked. In parallel to the actuation of its motors that drive the robot to and fro along two railways, the available energy supplies the pumps that periodically rehydrate the cathode and recirculate the substrate from a central digester to the anodic chambers of the ODC-MFCs. Despite careful design of the robot morphology and the use of low-power electronic solutions for the robot's actuation, sensing, and control, a few seconds of activity require several minutes of recharge. Therefore, the limitations due to the extremely low power generation force the robot to the exploitation of cycles of full charge and discharge of the energy accumulated across the capacitor. The current physical prototype robot lives a highly protected and controlled existence within an incubator, subject to direct human support. Nevertheless, its developers are ready to release its successors into semi-natural environments, thus demonstrating the robot's capacity for energy autonomy, that is, the capacity to provide for its own energy needs with no human intervention.

#### 3.2 A Foreseeable Future

In simulation, we can scale up the number of ODC-MFCs units that currently power EcoBot III. For example, we used the ODC-MFC model to power a simulated *e-buck* robot with 600 MFCs. The robot, in its basic configuration, sensed its environment through its sound, infrared, and light sensors. The robot's energy demand can be estimated based on the technical characteristics of its physical actuators (two stepper motors driving its wheels) [33].

Within its environment the robot could find sources of food and water. Two recharging areas, one for water (marked by a light source) and one for food (marked by a sound source), would instantaneously refill the associated tank upon the robot's entering them. Since the ODC-MFCs were the robot's only sources of energy, the maintenance of a high level of hydration and chemical-bond energy in its virtual digester allowed for higher available power. A deficit in water and food intake (both hydration and chemical-bond energy in the substrate were subject to decay) entailed incapacity for further movement and for further support of the anodic bacterial ecology (death).

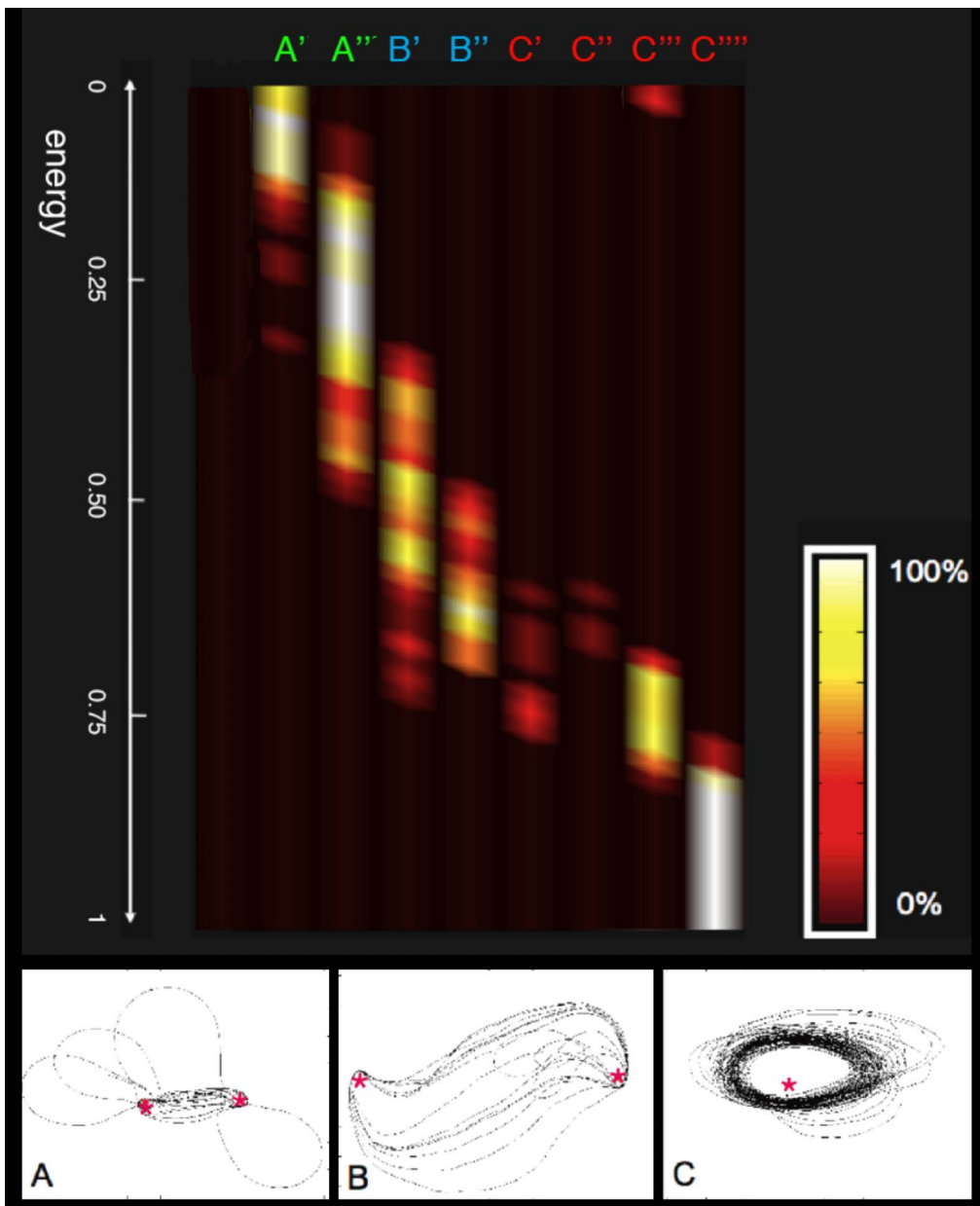


Our simulated robot was controlled by an artificial neural network (ANN). We tested several configurations of feedforward and recurrent ANNs. Their synaptic weights and biases were adapted by evolutionary algorithms [17]. The simple fitness function rewarded movement outside the recharging area (the rationale was simply to force motor activation and, consequently, energy expenditure). Nevertheless, no explicit information was provided about the existence and the meaning of the recharging areas. During its artificial evolution, the population of controllers would simply experience the access to the recharging area as an opportunity for an extended and energetically richer life. In virtue of this choice, we abandoned rigid control over the adaptive process. In other words, we sought to avoid imposing our own ontological perspective of the problem, by using a *generic* fitness to drive the evolutionary algorithm. This choice tends to promote self-organized solutions to the task [34].

Obviously, our choice about the number of on-board ODC-MFCs maintained the robot under mild energy constraints while it operated in dynamical engagement with its environment. In this case, the situation for an ODC-MFC-powered robot is not much different from that for a battery-powered robot (endowed with an undersized battery) that could find energy recharge inside its environment.

The role of the ODC-MFCs in our setup is twofold. Firstly, we can interpret it as an *artificial metabolism* that relates energy to the two essential variables of the system (level of hydration and of chemical-bond energy in the substrate). This provides the system with a set of metabolic signals that are directly connected to the intrinsic “well-being” of the robot. Secondly, the living bacterial colony in the anode provides the system with a component that imbues a certain level of *biological causal powers* [8, 15, 58]. These observations, together with energy scarcity, lead during the simulated evolutionary process to specific behavioral implications that we are about to explore:

- Adaptive forces, in this case evolutionary pressure, promote convergence toward behaviors that most effectively trace and exploit the environmental resources (food and water). In case the body morphology could also be adapted by evolutionary algorithms (e.g., [9]), this would be synergistic with the evolution of the neurocontroller. The interaction of more complex controllers and morphologies tends to develop energy-efficient behaviors. For example, we have shown how a less energetically demanding ocular actuation might be selected for an initial screening of the environmental scene before direct engagement in action for a decision-making task [28]. A similar strategy might involve abstract planning and thought [30].
- The variables (food and water levels) that are essential to the viability of the system (EVs in Ashbyian terminology) are its control parameters [18, 24]. This showed very clearly in a simplified experiment, where we only had one EV (energy level) subject to an arbitrary linear decay and a similar environmental interaction to provide recharge. In our analysis, we left a successfully evolved robot free to roam in its environment after clamping the value of its EV (i.e., overriding both the natural discharge and the environmental recharge). By a systematic exploration of the possible energy levels, we showed how their value dynamically reconfigured the phase space of the dynamic system constituted of the robot’s body, neurocontroller, and environment. We classified a set of eight behavioral attractors, and we demonstrated their distribution as a function of the energy level [31]. A simplified illustration of this distribution is given in Figure 3. The robot displayed two exploratory behaviors to find energy sources in the environment. These behaviors were used when the robot was in the condition of energy deficit (type A behaviors). Four behaviors were local, used by the robot at high levels of energy to remain close to the potential energy source (type C). Finally, two were hybrid behaviors, sharing characteristics with both exploratory and local behaviors and used for intermediate levels of energy (type B). The selection of the particular behavioral attractor followed the normal laws of dynamic systems: Falling on one behavioral attractor rather than another depended on the robot’s starting position and on the integrated effects of noise. This mechanism implemented a self-organized *dynamic action*



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Figure 3. *Lower panels:* Sample spatial trajectories for the three classes of behaviors observed in clamped conditions after transient exhaustion: exploratory behaviors (panel A), local behaviors (panel C), and hybrid forms (panel B). In the online version, potential energy rechargers (i.e., the positions of the light sources) are indicated by red stars. For better resolution, the icons representing each class of trajectories zoom on the area of main interest surrounding the light sources. *Top panel:* The intensity of the pixels for each column (corresponding to attractors belonging to classes A–C, as specified by their labels on the top row) represents the relative frequency of the behavioral attractor as a function of the energy level. For example, an energy level of 0.7 leads to the expression of attractor C''' (in 70% of the replications), C' (20%), or B' (10%). For energy levels in the interval [0.0, 0.4] we can observe a clear dominance of attractors in class A. A similar dominance in the energy interval [0.7, 1.0] is shown by attractors in class C. The hybrid forms in class B characterize intermediate energy levels. Adapted from [31].



*selection mechanism* that elicited the subset of behavioral attractors as appropriate to the current context.

More recently, a similar mechanism also emerged for the system with two EVs (food and water levels) [33]. In this case, water and food areas were the focus of two basins of attraction. In clamped conditions, the control parameters modulated the ratio of water to food access, that is, the probability of a transition from one to the other basin of attraction.

- Depending on the interplay of environmental conditions and physical characteristics, the viable robots could manifest a wide range of behavioral diversity. For example, we have shown how they could rely on bursts of maximal power activation, leading to cycles of full energy recharge and distribution, or on more conservative, submaximal motor activation that would tend to maintain an instant balance between the generated and utilized power [33]. In other words, pulsing and continuous actuation would be two qualitative behavioral options in front of an identical quantitative energy balance. This result, reminiscent of the range of different behavioral strategies (e.g.) in three-toed sloths, wolves, cheetahs, and crocodiles, is summarized in Figure 4.

Further consequences appear more specific to MFC-operated systems:

- The meaning of the terms like “water” and “food” is grounded in the viable dynamics of the robot. Following Varela [51, p. 79], whose words should not be interpreted in a functionalist perspective, but rather as emphasizing the role of dynamical interaction: “There is no food significance in sucrose except when a bacteria swims upgradient and its metabolism uses the molecule in a way that allows its identity to continue.” Of course, the same might apply for “energy source” in the case of a battery-operated robot. Nevertheless, more sophisticated sets of sensors (e.g., electronic noses) might be integrated in the robot design to provide an elementary chemical analysis of the available resources. On this basis, the robot might classify the potential food and develop a system of preferences related to the experienced energy content of the available resources (a comparison of energy associated with different food sources is available in [30]). Thus, the potential for the emergence of proto-meaning appears naturally richer in the case ODC-MFC-powered robots.
- EcoBot III is now provided with a solid-waste excretion mechanism to periodically excrete solid sediments from the substrate that served the anodic chambers. Apparently, such solid wastes possess fertilizing properties. The robot might learn how to spatially organize areas dedicated to its foraging and excretions, and temporally rotate them in order to achieve more prosperous harvests.

### 3.3 A Long-Term Prospect

Finally, in simulation we can also increase the number of on-board ODC-MFCs further, so that they could promptly satisfy virtually any power demand by the robot they serve over extended periods of time. This possibility links to a serious effort toward miniaturization in MFC research. In fact, Ieropoulos, Greenman, and Melhuish [20] showed how small-scale MFCs tend to produce higher power density. In some types of MFC, such a miniaturization might be pushed to microscopic limits ( $\mu\text{m}$ ), as shown by Kim et al. [25]. If experimentally further supported, this scenario entails the design of artifacts supplied with large numbers of on-board miniature cells connected in appropriate stack configurations to implement a distributed energy system, largely reminiscent of the distributed energy mechanisms in biological cells.

After the constraints imposed by energy scarcity have been removed, would our MFC powered system differ in any significant way from energy autonomous robots energized by more conventional

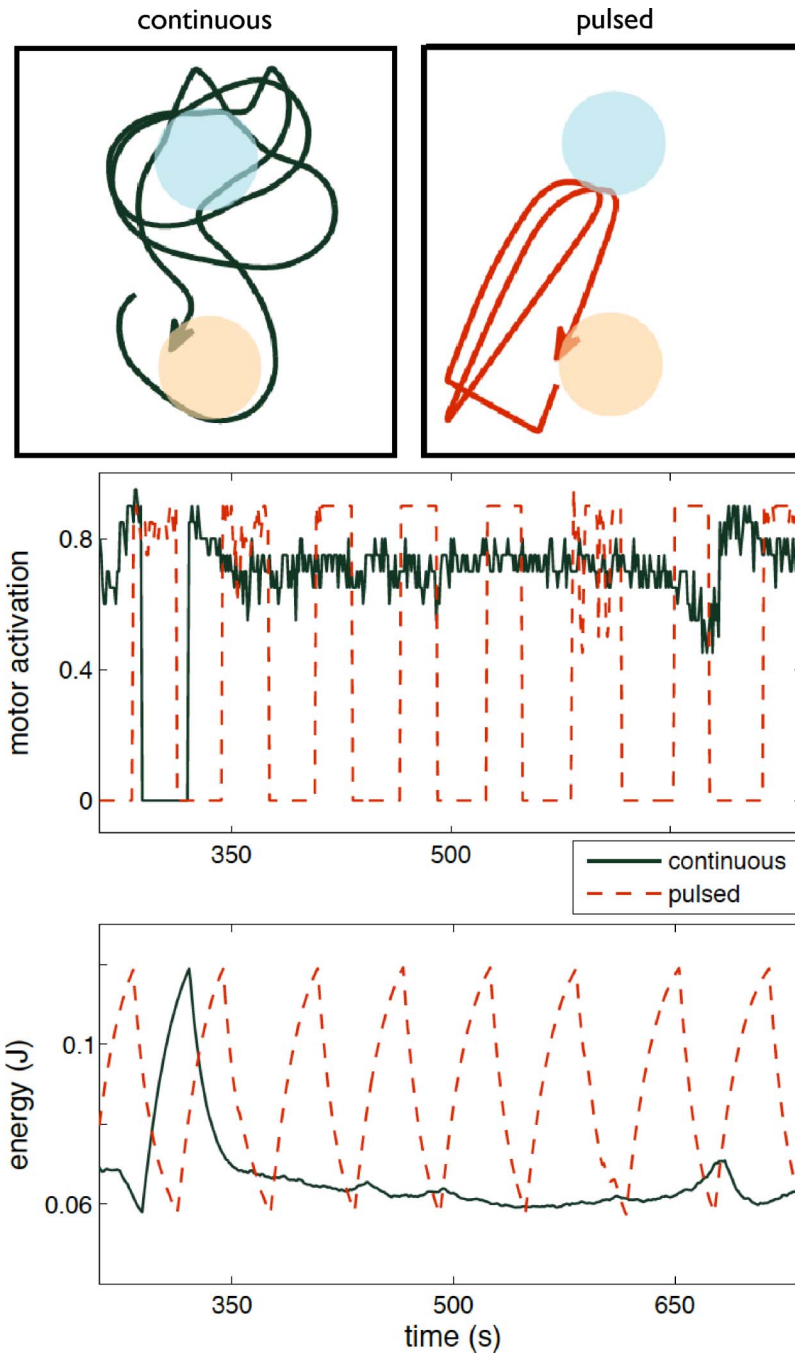


Figure 4. *Top panels:* Examples of continuous (left) and pulsed (right) robot trajectories. In each panel, on entering the higher (the lower) circle, the robot receives hydration (fresh substrate). *Lower panels:* Motor activation (top) and energy level (bottom) for continuous (continuous curves) and pulsed (dashed curves) behavior. Adapted from [33].

sources (e.g., rechargeable batteries)? Firstly, we could answer by pointing to the intrinsic thermodynamic irreversibility of, for example, common rechargeable batteries (the property that forces us to dispose of exhausted batteries). On the other hand, in principle, the bacterial colony in the MFCs’ anode constitutes a rather robust and dynamically self-sustained system, as long as it can satisfy its

need for biomass and water. Secondly, a careful design of the MFC-powered robot's body (including behavioral consequences to cope with smaller digesters) might overcome the weight and bulkiness of battery-operated systems.

Yet a further and most important distinction is possible. Both MFC and conventionally powered robots rely on the coupling with an external environment. In the case of conventional systems, they are coupled with an *artificial* environment, that is, an environment that must be provided with substantial energy and human supervision in order to compensate for its natural entropic drift. Otherwise, it dissipates. For example, think of our modern cities, generously offering easy access to power sockets. Any image of the Roman Forum should provide enough evidence about the dissipative phenomenon in question. On the other hand, MFC-powered systems can be coupled to a *natural* environment. Natural environments require energy too: nevertheless, they admit (and rather seem to favor) lack of human intervention. Therefore, battery- and ODC-MFC-powered robots bring forth a different kind of energy autonomy, for they seem to offer drastically different capacities and potentials.

There is a further peculiar constraint that our setup poses on the kind of autonomy that is possible for our robot and that differentiates it from a battery-powered one. Consider a population of ODC-MFC-powered robots. Each member of the population still crucially depends on the resources at hand in its environment. It is viable as long as its behavior promotes a balanced and sustained relationship with its environment, and the same applies to the whole population within the space-time horizon of this robotic species. Behaviors that are disruptive of the ecological balance would be irreconcilable with long-term viability. In other words, the viable robot and population would be ecologically grounded in its environment, and its specific form of autonomy would be constrained by the maintenance of its ecological balance. By *ecological autonomy* we mean a form of energy and motivational autonomy that is crucially constrained by the demands of the agent's viable integration in its natural environment over time.

#### 4 Discussion and Conclusions

In this article, we have presented simulations of a robotic system subject to energy limitations that can capitalize on these restrictions, as it adapts to develop a rich behavioral diversity. The simulated agent in our experiments constitutes a biomechatronic symbiont. A conventional e-puck robot derives the energy for its actuation from a stack of ODC-MFCs, mathematically modeled on the basis of an actual physical prototype. In our simulated robotic setup, the ODC-MFC energy generation system represents a basic abstraction of a metabolic system, thus allowing the study of the interaction between sensorimotor and metabolic dynamics. The use of simulation offers the opportunity for the systematic study of different scenarios, where the energy constraints can be increased or relaxed at will. The living bacterial colony in the ODC-MFC anode endows our biomechatronic hybrid system with some level of biological causal powers that is unprecedented in robotics.

The use of hybrid systems, made of living components coupled to electronic or biomechatronic devices, is not new. For example, Ruaro, Bonifazi, and Torre [43] used neural cultures coupled to traditional electronic systems via multielectrode arrays in order to perform intrinsically parallel basic image processing and pattern recognition. A similar technology was used by Bakkum et al. [2] to control the navigation of a simple robot through a culture of dissociated cortical neurons. An analogous result was reported by Reger et al. [42], who established a two-way communication between a dissected portion of the brain stem of a sea lamprey and a Khepera robot. Similarly, the idea of a control parameter that dynamically reshapes the phase space of the system is not new in the robotic literature. For example, a *recurrent neural network with parametric bias* (see [47, 48]) was used to control the switching between simple behavioral attractors in a basic humanoid robot handling a ball [22].

Nevertheless, the system that we have introduced in the previous sections does bring forth an element of novelty. The primary motivation of this article is bringing that to the fore. In our system we can distinguish between two kinds of signals. First, sensory and motor information, at relatively

*high frequency*, relate to the ongoing interaction between the robot and its environment. The typical evolution of this signal follows a time scale on the order of magnitude of seconds. For example, the robot can reorient its light sensor toward a source of light and bring it to saturation in a fraction of a second. The same can happen with the activation of its motors. On the other hand, we also recognize *low-frequency* signals, characteristically associated with the artificial metabolism of the robotic system constituted by the stack of ODC-MFCs. Typically, signals associated with the ODC-MFC dynamics have a time scale in the hundreds of minutes. Indeed, the sensorimotor signal is the information that qualifies the study of perception, action, and their interaction. Crucially, the low-frequency metabolic signal, by means of the evolutionary adaptation of the neurocontroller, associates the contingent flow of sensorimotor information to the non-negotiable essence of adaptivity, that is, the agent's well-being. Blindness to this fact amounts to trapping the study of cognitive phenomena in contingent and local dynamics, while neglecting that, on a broader scale, cognition amounts to the deployment of sophisticated strategies for survival.

Indeed, this feature is not uniquely characteristic of our own hybrid model. Bedau et al. [3, p. 91] draw a useful distinction between *primary living technology*—that is, systems whose lifelike properties are “constructed out of components that never were alive”—and *secondary living technology*, where such properties “depend primarily on the antecedent lifelike properties” of their components. While our model undoubtedly belongs to the latter class, systems belonging to the former might well carry analogous types of information, capable of orienting the contingent sensorimotor flow toward paths that promote viability and general well-being of the system. Taking this point of view, we maintain a neutral stance with respect to the kinds of artificial cognitive systems that are most suitable for the study of cognition, as long as they are capable of producing the basic kind of biological causal power that we have just illustrated.

In fact, more theoretical arguments advocate that metabolic processes of the kind that we have described in this article might play a fundamental role in the emergence of cognition. Affect is a powerful motivator of future behavior [26]. Somatic theories of emotions (e.g., [14]) consider emotions as emerging from tangible processes, physically rooted in the body and objectively measurable. Searle [44] argued that current cognitive architectures lack the “biological causal power” to convincingly replicate biological intentionality, the basic property for cognitive processes. In a similar and more analytical vein, Bickhard [8] described the biological foundations for the emergence of cognition. According to his approach, namely *interactivism*, there are three basic necessary conditions for a cognitive system. Ordered according to increasing strictness, they are [8]:

1. the system must display sustained existence *far from equilibrium*, for example, as in Rayleigh-Bérnard convection cells, where regular patterns of convection cells form on the surface of a fluid maintained under an appropriate heat differential between its bottom and its open surface;
2. the system must be *self-maintenant*, that is, as in a candle flame, the system must be capable of regenerating the conditions for the process to occur;
3. the system must be *recursively self-maintenant*, that is, it must be capable of maintaining the property of being self-maintenant (Bickhard [8] gives the example of a “science-fictional candle flame” that can refuel when the candle is almost consumed).

According to Bickhard [8], classical and connectionist computers can merely simulate but not instantiate cognitive processes, because, unlike organisms, they have no significant properties of self-maintenance and openness (i.e., they do not significantly interact with their environment). On the contrary, the form that being far from equilibrium takes in living systems is a deep ontological condition, rather than an incidental fact, due to the thermodynamical irreversibility of the process. In other words, once the far-from-equilibrium living process is sufficiently perturbed, it cannot be restarted, which is different from a machine that operates far from equilibrium. Bickhard [8] concedes that battery-operated robots can be considered as being, in some minimal and marginal

sense, far from equilibrium, self-maintenant, and recursively self-maintenant. Nevertheless, the reversibility of the machine process marginalizes the normative aspects of their relation to the environment [8]. According to this analysis, far-from-equilibrium and recursively self-maintenant systems that do not benefit from such reversibility, analogously to the hybrid system that we describe in this article, seem more suitable models for the emergence of meaning and cognition.

The metabolic signal plays a crucial role in providing the cognitive system with a *motivational level*. Parisi and Petrosino [37] highlight the insufficiency of (external) sensory stimuli and the centrality of (internal) motivations to determine behavior. The motivational state of an animal (i.e., its behavioral bias toward eating rather than drinking, or mating, or escaping predators) determines the conditions for the selection of an actual behavior, a choice that is pertinent to the *cognitive level*: “motivational decisions are super-ordinate with respect to action selection” [37, p. 455]. Figure 3 can be reinterpreted in this light. In this scenario, the energy level sets the system in different motivational states. Within this main motivational condition, the actual robot’s dynamics are selected according to the laws of dynamical systems, for a number of behavioral attractors are competing at each level of energy.

Finally, we should also observe how our experimental setup emphasizes the constructive role of *energy*. Strangely, contemporary robotics has almost entirely neglected energy, unless as an annoying problem that imposes strong and undesirable constraints on the robot’s autonomy. Nevertheless, the role of biological metabolism is not limited to the assimilation and synthesis of the basic material needed for the continuous organismic self-production. It also makes available a net amount of energy that can be used to support sensory, motor, and nervous activity. During the evolutionary adaptation of the neurocontroller of our simulated robot, the interaction between energy restriction and biological causal powers plays a fundamental role and endows the robot with characteristic and peculiar properties. This interaction creates a powerful pressure that tends to select effective (in the sense of viable) and energy-efficient behaviors (the same might apply in the case of evolvable morphology). It also determines the conditions for a rich collection of behaviors and behavioral strategies. The metabolic signals, directly connected to the basic needs for the viability of the system, can be readily interpreted as its control parameters, the crucial variables that dynamically select the subset of behaviors that are appropriate to the specific context. In parallel, biological causal powers constrain the robot’s autonomy to behaviors that promote an ecologically balanced integration in its environment and the grounding of meaning, relative to the aspects of the environment that are most salient for robot viability. In our future work, the potential of energy as a powerful kind of synthetic information that can be effectively used to drive adaptation on different time scales will be further developed.

## References

1. Ashby, W. R. (1960). *Design for a brain* (2nd ed.). New York: Wiley.
2. Bakkum, D., Shkolnik, A., Ben-Ary, G., Gamblen, P., DeMarse, T., & Potter, S. (2004). Removing some A from AI: Embodied cultured networks. In F. Iida, R. Pfeifer, L. Steels, & Y. Kuniyoshi (Eds.), *Embodied artificial intelligence* (pp. 130–145). Berlin: Springer.
3. Bedau, M. A., McCaskill, J. S., Packard, N. H., & Rasmussen, S. (2010). Living technology: Exploiting life’s principles in technology. *Artificial Life*, 16(1), 89–97.
4. Bedau, M. A., McCaskill, J. S., Packard, N. H., Rasmussen, S., Adami, C., Green, D. G., Ikegami, T., Kaneko, K., & Ray, T. S. (2000). Open problems in artificial life. *Artificial Life*, 6(4), 363–376.
5. Beer, R. D. (1995). Artificial intelligence: A dynamical systems perspective on agent-environment interaction. *Artificial Intelligence*, 72, 173–215.
6. Beer, R. D. (2000). Dynamical approaches to cognitive science. *Trends in Cognitive Sciences*, 4(3), 91–99.
7. Beer, R. D. (2003). The dynamics of active categorical perception in an evolved model agent. *Adaptive Behavior*, 11(4), 209–243.
8. Bickhard, M. (2009). The biological foundations of cognitive science. *New Ideas in Psychology*, 27(1), 75–84.



9. Bongard, J. (2011). Morphological change in machines accelerates the evolution of robust behavior. *Proceedings of the National Academy of Sciences of the U.S.A.*, 108(4), 1234–1239.
10. Chemero, A. (2009). *Radical embodied cognitive science*. Cambridge, MA: MIT Press.
11. Chiel, H., & Beer, R. D. (1997). The brain has a body: Adaptive behavior emerges from interactions of nervous system, body and environment. *Trends in Neurosciences*, 20(12), 553–557.
12. Clark, A. (1997). *Being there: Putting brain, body, and world together again*. Cambridge, MA: MIT Press.
13. Damasio, A. (2000). *The feeling of what happens: Body and emotion in the making of consciousness*. New York: Mariner Books.
14. Damasio, A. (2003). *Looking for Spinoza: Joy, sorrow, and the feeling brain*. New York: Mariner Books.
15. Di Paolo, E. (2003). Organismically-inspired robotics: Homeostatic adaptation and natural teleology beyond the closed sensorimotor loop. In K. Murase & T. Asakura (Eds.), *Dynamical systems approach to embodiment and sociality* (pp. 19–42). Adelaide, Australia: Advanced Knowledge International.
16. Gates, B. (2007). A robot in every home. *Scientific American*, 296(1), 58–65.
17. Goldberg, D. E. (1989). *Genetic algorithms in search, optimization, and machine learning*. Reading, MA: Addison-Wesley Professional.
18. Haken, H. (2004). *Synergetics: Introduction and advanced topics*. Berlin: Springer.
19. Harkema, S., Gerasimenko, Y., Hodes, J., Burdick, J., Angeli, C., Chen, Y., Ferreira, C., Willhite, A., Rejc, E., Grossman, R. G., & Edgerton, V. R. (2011). Effect of epidural stimulation of the lumbosacral spinal cord on voluntary movement, standing, and assisted stepping after motor complete paraplegia: A case study. *Lancet*, 377(9781), 1938–1947.
20. Ieropoulos, I., Greenman, J., & Melhuish, C. (2010). Improved energy output levels from small-scale microbial fuel cells. *Bioelectrochemistry*, 78(1), 44–50.
21. Ieropoulos, I., Greenman, J., Melhuish, C., & Horsfield, I. (2010). EcoBot-III: A robot with guts. In H. Fellermann, M. Dörr, M. Hanczyc, L. L. Laursen, S. Maurer, D. Merkle, P.-A. Monnard, K. Sty, & S. Rasmussen (Eds.), *Artificial Life XII* (pp. 733–740).
22. Ito, M., Noda, K., Hoshino, Y., & Tani, J. (2006). Dynamic and interactive generation of object handling behaviors by a small humanoid robot using a dynamic neural network model. *Neural Networks*, 19(3), 323–337.
23. James, W. (1890). *The principles of psychology, Vol. 2*. New York: Henry Holt and Co.
24. Kelso, J. A. S. (1995). *Dynamic patterns: The self-organization of brain and behavior*. Cambridge, MA: MIT Press.
25. Kim, H.-H., Mano, N., Zhang, Y., & Heller, A. (2003). A miniature membrane-less biofuel cell operating under physiological conditions at 0.5V. *Journal of the Electrochemical Society*, 150, A209–A213.
26. LeDoux, J. (1996). *The emotional brain*. New York: Simon & Schuster.
27. Logan, B. E., Hamelers, B., Rozendal, R., Schröder, U., Keller, J., Freguia, S., Aelterman, P., Verstraete, W., & Rabaey, K. (2006). Microbial fuel cells: Methodology and technology. *Environmental Science and Technology*, 40(17), 5181–5192.
28. Lowe, R., Montebelli, A., Ieropoulos, I., Greenman, J., Melhuish, C., & Ziemke, T. (2010). Grounding motivation in energy autonomy: A study of artificial metabolism constrained robot dynamics. In H. Fellermann, M. Dörr, M. Hanczyc, L. L. Laursen, S. Maurer, D. Merkle, P.-A. Monnard, K. Sty, & S. Rasmussen (Eds.), *Artificial Life XII* (pp. 725–732).
29. McFarland, D. (2008). *Guilty robots, happy dogs: The question of alien minds*. Oxford, UK: Oxford University Press.
30. Melhuish, C., Ieropoulos, I., Greenman, J., & Horsfield, I. (2006). Energetically autonomous robots: Food for thought. *Autonomous Robots*, 21, 187–198.
31. Montebelli, A., Herrera, C., & Ziemke, T. (2008). On cognition as dynamical coupling: An analysis of behavioral attractor dynamics. *Adaptive Behavior*, 16(2–3), 182–195.
32. Montebelli, A., Ieropoulos, I., Lowe, R., Ziemke, T., Melhuish, C., & Greenman, J. (2011). An oxygen-diffusion cathode MFC model for simulation of energy-autonomous robots. *Submitted for journal publication*.



33. Montebelli, A., Lowe, R., Ieropoulos, I., Melhuish, C., Greenman, J., & Ziemke, T. (2010). Microbial fuel cell driven behavioral dynamics in robot simulations. In H. Fellersmann, M. Dörr, M. Hanczyc, L. L. Laursen, S. Maurer, D. Merkle, P.-A. Monnard, K. Sty, & S. Rasmussen (Eds.), *Artificial Life XII* (pp. 749–756).
34. Nolfi, S. (1998). Evolutionary robotics: Exploiting the full power of self-organization. *Connection Science*, 10(3–4), 167–184.
35. Nolfi, S., & Floreano, D. (2000). *Evolutionary robotics: The biology, intelligence, and technology of self-organizing machines*. Cambridge, MA: MIT Press.
36. Parisi, D. (2004). Internal robotics. *Connection Science*, 164, 325–338.
37. Parisi, D., & Petrosino, G. (2010). Robots that have emotions. *Adaptive Behavior*, 18(6), 453–469.
38. Pfeifer, R., & Bongard, J. C. (2006). *How the body shapes the way we think*. Cambridge, MA: MIT Press.
39. Pfeifer, R., & Gómez, G. (2005). Interacting with the real world: Design principles for intelligent systems. *Artificial Life and Robotics*, 9(1), 1–6.
40. Pickering, A. (2010). *The cybernetic brain: Sketches of another future*. Chicago: University of Chicago Press.
41. Rabaey, K., & Verstraete, W. (2005). Microbial fuel cells: Novel biotechnology for energy generation. *Trends in Biotechnology*, 23(6), 291–298.
42. Reger, B. D., Fleming, K. M., Sanguineti, V., Alford, S., & Mussa-Ivaldi, F. A. (2000). Connecting brains to robots: An artificial body for studying the computational properties of neural tissues. *Artificial Life*, 6(4), 307–324.
43. Ruaro, M. E., Bonifazi, P., & Torre, V. (2005). Toward the neurocomputer: Image processing and pattern recognition with neuronal cultures. *IEEE Transactions on Bio-medical Engineering*, 52(3), 371–383.
44. Searle, J. R. (1980). Minds, brains, and programs. *Behavioral and Brain Sciences*, 3(3), 417–457.
45. Shapiro, L. (2011). *Embodied cognition*. Oxford, UK: Routledge.
46. Skarda, C. A., & Freeman, W. J. (1987). How brains make chaos in order to make sense of the world. *Behavioral and Brain Sciences*, 10(2), 161–195.
47. Tani, J. (2003). Learning to generate articulated behavior through the bottom-up and the top-down interaction processes. *Neural Networks*, 16, 11–23.
48. Tani, J., & Ito, M. (2003). Self-organization of behavioral primitives as multiple attractor dynamics: A robot experiment. *IEEE Transactions on Systems, Man, and Cybernetics—Part B: Cybernetics*, 33(4), 481–488.
49. Thelen, E., & Smith, L. B. (1994). *A dynamic systems approach to the development of cognition and action*. Cambridge, MA: MIT Press.
50. van Gelder, T. (1995). What might cognition be, if not computation? *The Journal of Philosophy*, 92(7), 345–381.
51. Varela, F. J. (1997). Patterns of life: Intertwining identity and cognition. *Brain and Cognition*, 34(1), 72–87.
52. Varela, F. J., Thompson, E. T., & Rosch, E. (1991). *The embodied mind*. Cambridge, MA: MIT Press.
53. Walter, W. G. (1950). Imitation of life. *Scientific American*, 182(5), 42–45.
54. Walter, W. G. (1951). A machine that learns. *Scientific American*, 185(2), 60–63.
55. Walter, W. G. (1963). *The living brain* (2nd ed.). New York: W. W. Norton.
56. Wiener, N. (1954). *The human use of human beings: Cybernetics and society*. Cambridge, MA: Da Capo Press.
57. Wilkinson, S. (2000). “Gastronome”—A pioneering food powered mobile robot. In *Proceedings of the 2000 LASTED International Conference on Robotics and Applications*.
58. Ziemke, T. (2008). On the role of emotion in biological and robotic autonomy. *BioSystems*, 91, 401–408.
59. Ziemke, T., & Lowe, R. (2009). On the role of emotion in embodied cognitive architectures: From organisms to robots. *Cognitive Computation*, 1(1), 104–117.

## Appendix: Equations of the ODC-MFC Model

We report below the set of equations for the ODC-MFC model, as thoroughly described in [32]. The values for the parameters that appear in the equations are reported in Table 1. Observe that the form of the model used in [33] differs from the one described here. The former model can be interpreted as the local linearization of the following equations.

### A.1 Electric Charge Balance

With reference to node  $\alpha$  in Figure 2,

$$\frac{V_0 - V_C}{R_i} = C \frac{dV_C}{dt} \quad (1)$$

### A.2 Dependence on Substrate

$$subst = 1 - \frac{t_s}{\tau_s} \quad (2)$$

where  $subst$  represents the current level of biochemical energy in the anodic substrate, and  $t_s$  is the time from the last replenishment of the anodic chamber with fresh substrate.

$$V_{0max} = q_{V_0} + m_{V_0} t_s \quad (3)$$

$$R_{imin} = q_{R_i} + m_{R_i} t_s. \quad (4)$$

### A.3 Dependence of Hydration on Time

$$hyd = \beta + \frac{\alpha_p}{1 + e^{\gamma_p(t_b - \delta_p)}} - \frac{\alpha_n}{1 + e^{\gamma_n(t_b - \delta_n)}} \quad (5)$$

where  $hyd$  represents the current level of hydration in the cathode, and  $t_b$  is the time from the last hydration.

### A.4 Dependence of $R_i$ and $V_0$ on Hydration

$$V_0 = V_{0max} - \alpha_{V_0} + \frac{\alpha_{V_0}}{1 - hyd^*} (hyd - hyd^*) \quad (6)$$

$$R_i = R_{imin} + \frac{\alpha_{R_i}}{1 - hyd^*} (1 - hyd). \quad (7)$$

### A.5 Energy Stored in the Capacitor

$$\varepsilon = \frac{1}{2} C V_C^2. \quad (8)$$

Table I. Suggested values for the parameters.

Parameter	Equation	Numerical value	Unit
$C$	1;8	0.0282	F
$\bar{\tau}_s$	2	60,000	min
$q_{V_0}$	3	3.2	V
$m_{V_0}$	3	-0.00000667	V/min
$q_{R_i}$	4	550	$\Omega$
$m_{R_i}$	4	0.0442	$\Omega$ /min
$\beta$	5	0.2	—
$\alpha_p$	5	1.9	—
$\alpha_n$	5	0.85	—
$\gamma_p$	5	0.0055	l/min
$\gamma_n$	5	0.031	l/min
$\delta_p$	5	710	min
$\delta_n$	5	600	min
$\alpha_{V_0}$	6	0.18	V
$\alpha_{R_i}$	7	320	$\Omega$

