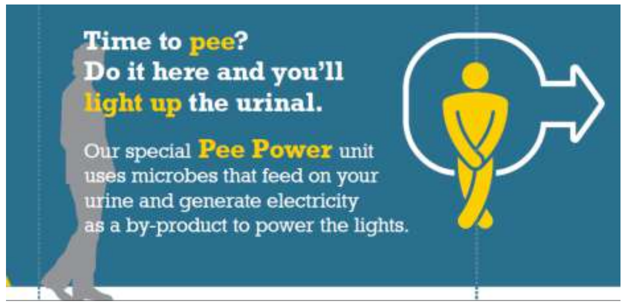
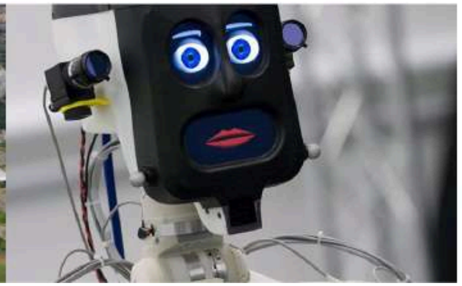
Microbial Fuel Cells for Robots and other Applications

Professor Ioannis A. Ieropoulos

ShanghAI Lectures, 28 November 2019



BRL Up Close



Motivation

photo courtesy of komahy.com

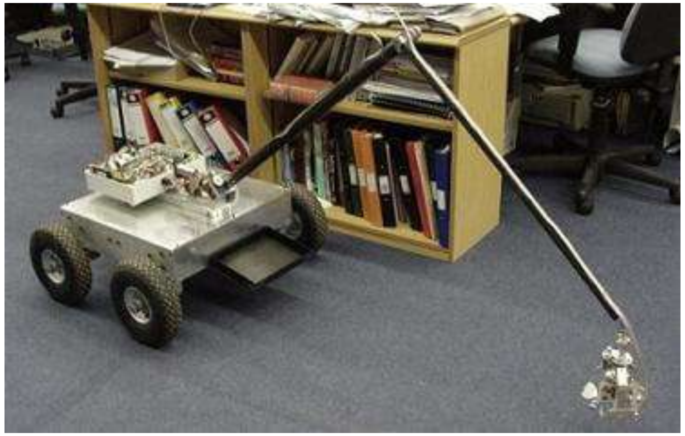
photo courtesy of K. Catania

photo courtesy of Prof. Renoux

Can we build robots that are energetically autonomous i.e. do not require human intervention?

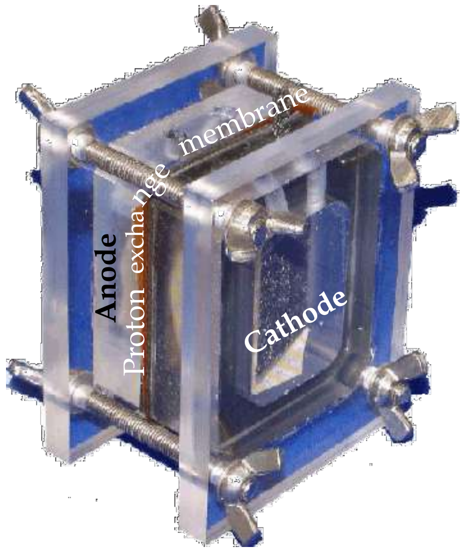
Energy autonomy - Microbial Fuel Cells

Bristol BioEnergy Centre

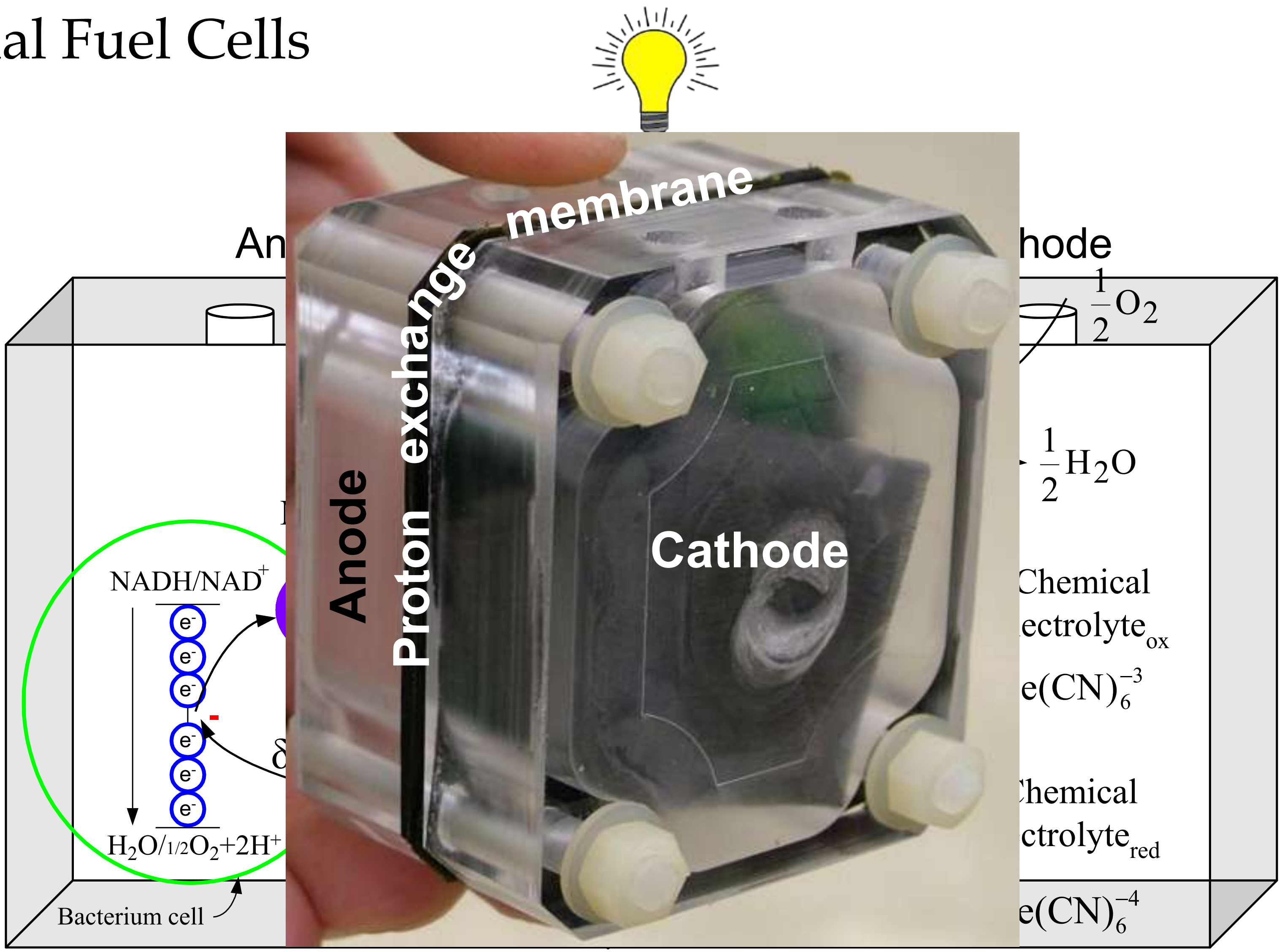


Slugbot - 2000

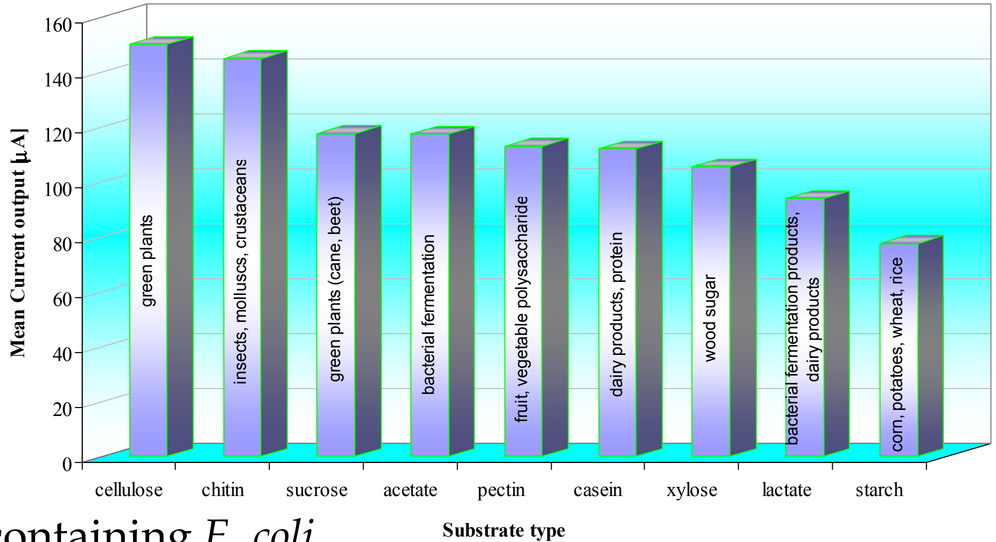
Gastrobot - 2000



Microbial Fuel Cells

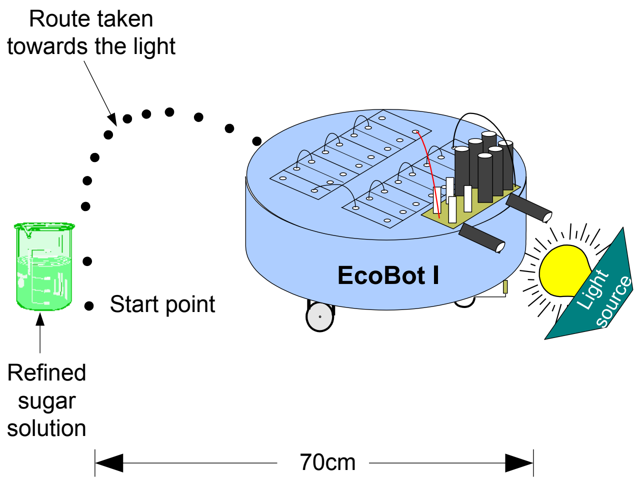


Implementation in Autonomous Robots: **EcoBot-I**

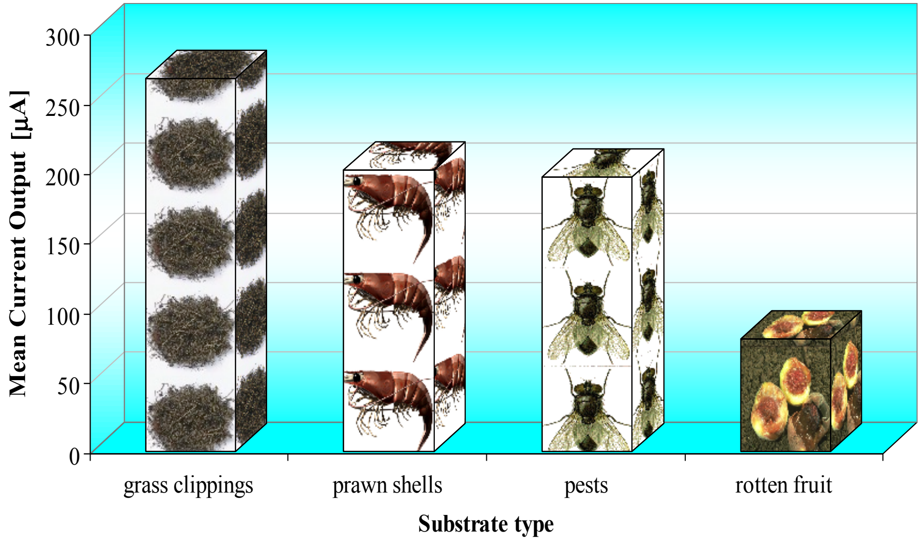


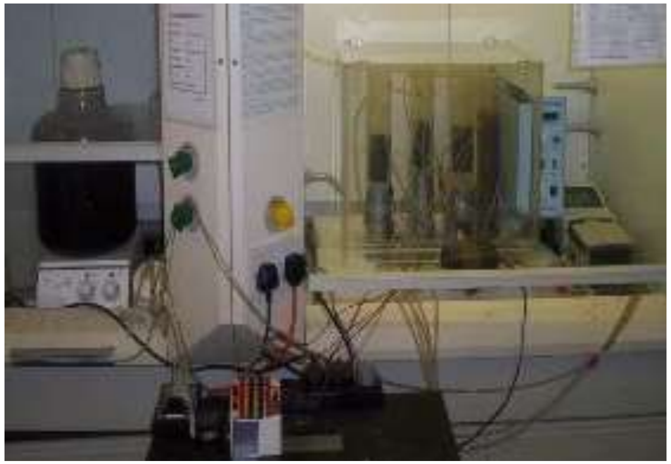
Artificial Life 2003, LNCS, Springer, pp. **792-799**

- 8 MFCs containing *E. coli*
  - 1 task: photo-taxis
- World's 2nd robot to employ MFCs
- World's 2nd robot to utilise a refined organic substrate
- World's 1st robot NOT to include conventional power supply



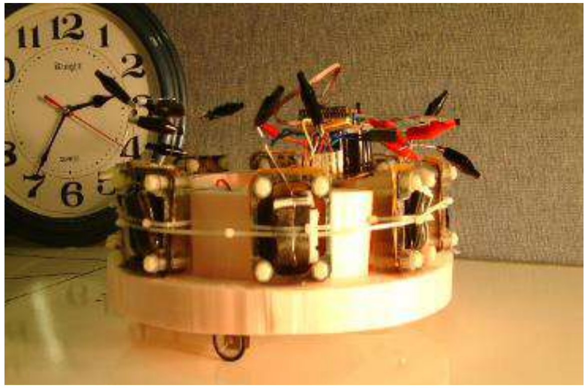
Feedstock profiling –unrefined/difficult substrates

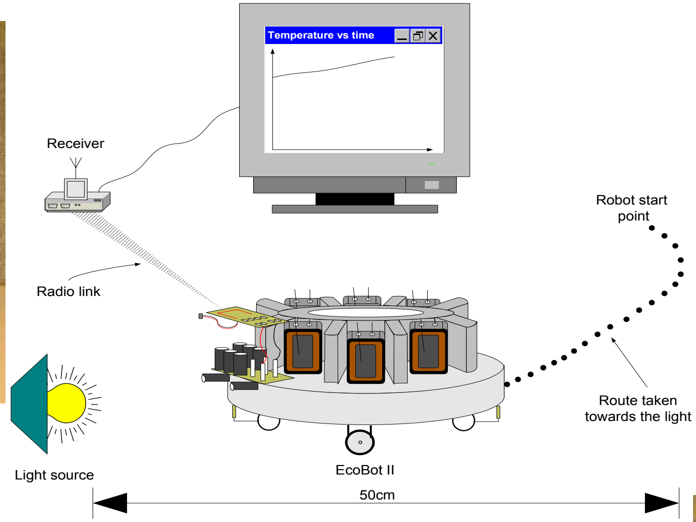




Insect digestion monitoring

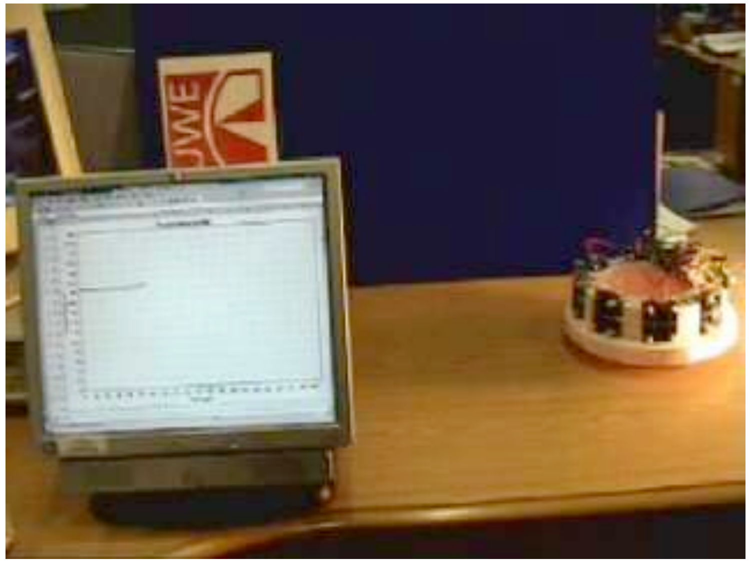
Implementation in Autonomous Robots: **EcoBot-II**



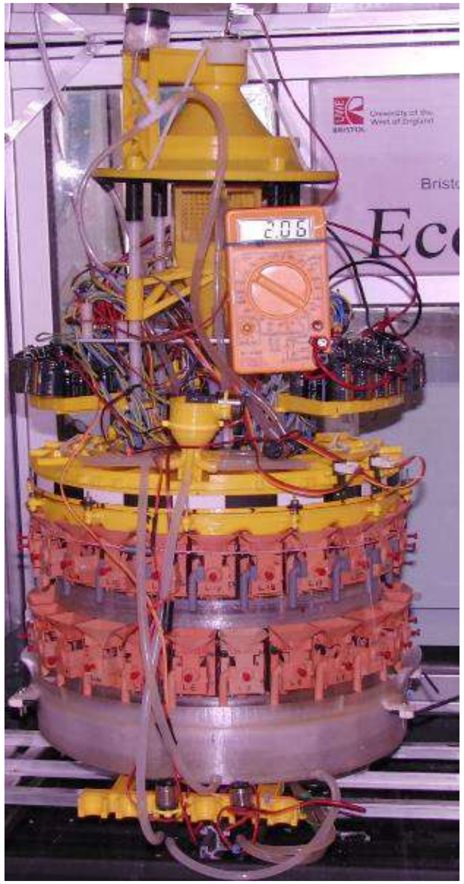


Autonomous Robots, 2006
21(3):187–198

- 8 MFCs containing sewage sludge microbes
- World's 1st to perform 4 tasks:
    - Sensing
    - Processing
    - Actuation (photo-taxis)
    - Communication
- World's 1st to 'eat' raw difficult substrate e.g. flies or rotten fruit
- World's 1st to employ the O_2 cathode



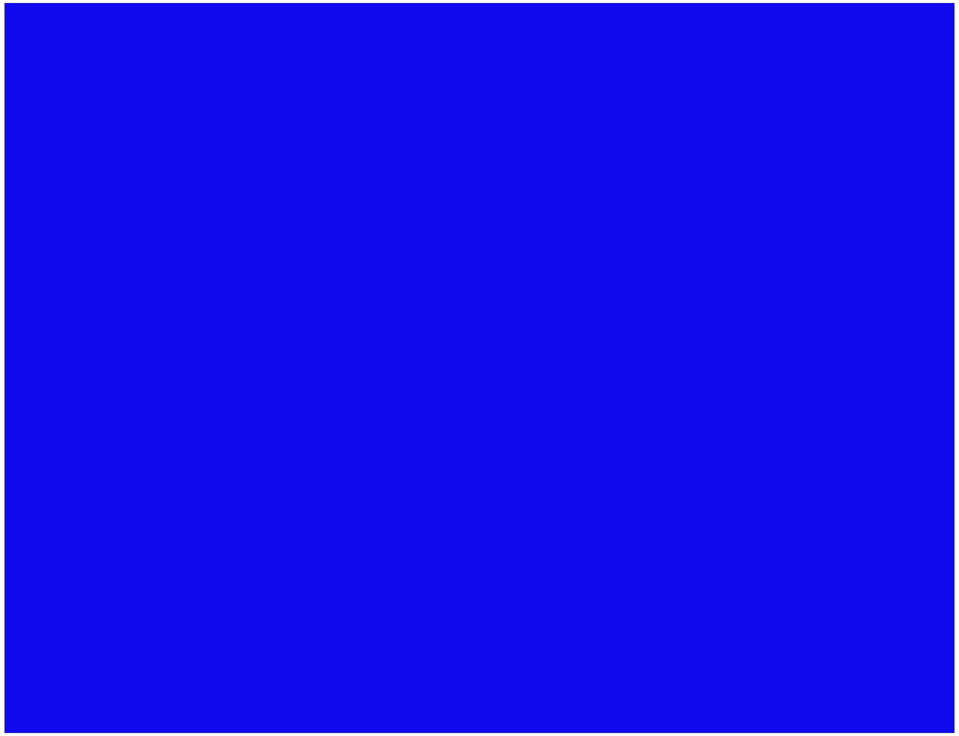
Implementation in Autonomous Robots: **EcoBot-III**



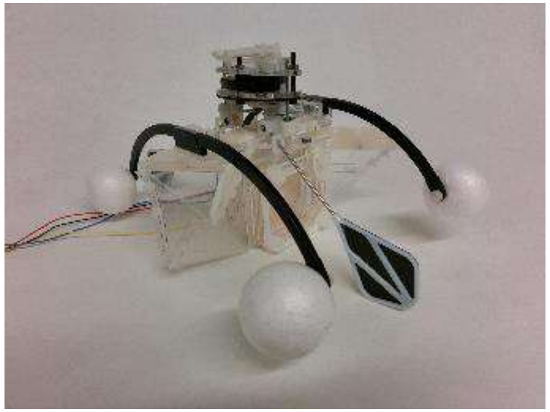
- 48 MFCs
- Own circulatory system for:

(i) Ingestion;
(ii) Digestion
(iii) Egestion

- World's 1st to collect its own food and water
- World's 1st to get rid of its own waste
- Telemetry
- *SymBots – symbiotic robots*



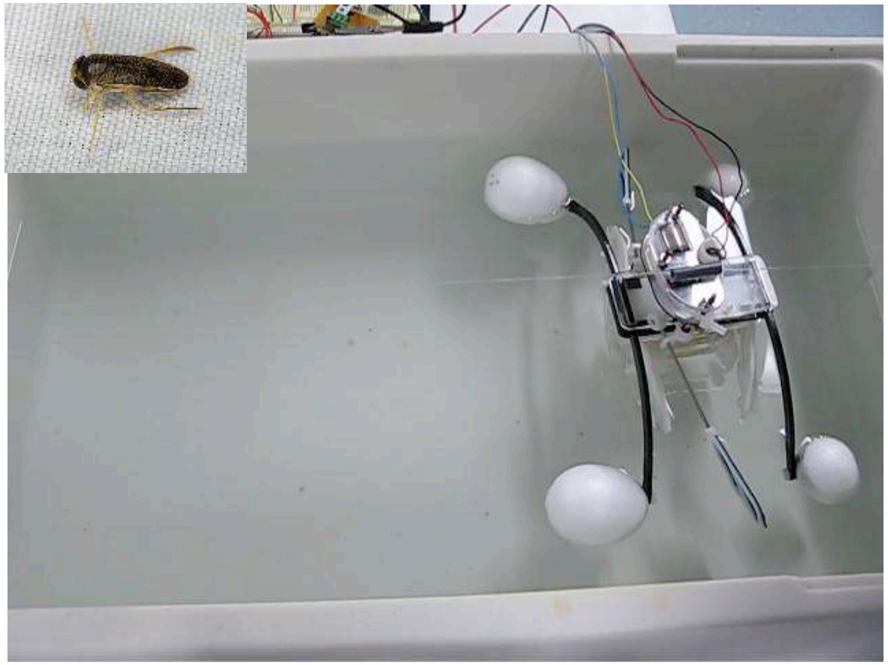
EcoBot-III, 2010; *Artificial Life'12*, MIT Press, pp. **733-740**



Exploiting morphology for the robot's actuation

Soft body which is actuated to open and close as a mouth for allowing liquid food to flow in in order to be digested by the MFCs aboard

IEEE Int Robots & Sys (IROS), 2015, 3888-3893



Electricity generation for mobile phones, wearables & lighting

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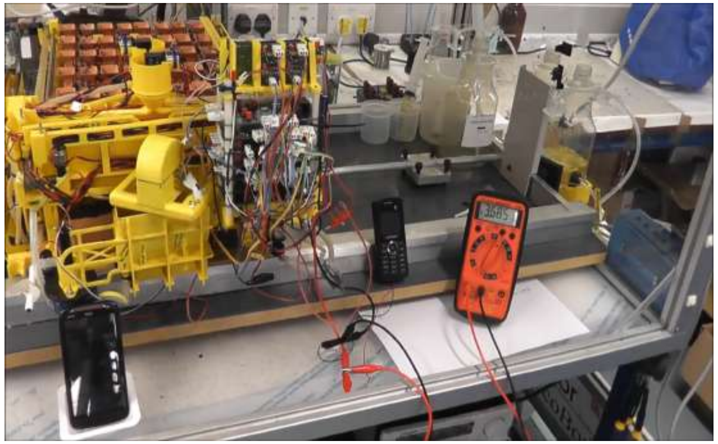
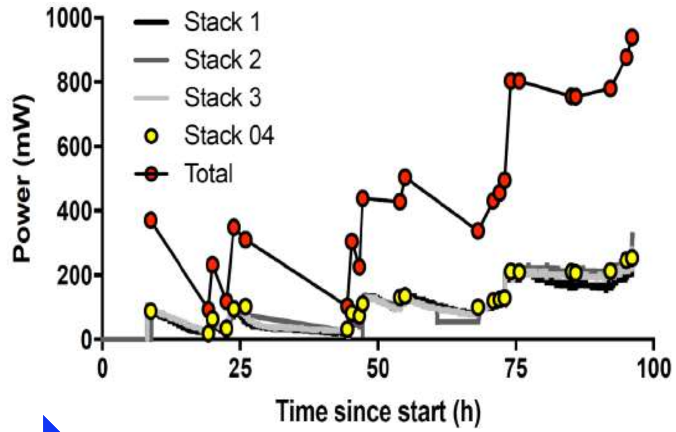
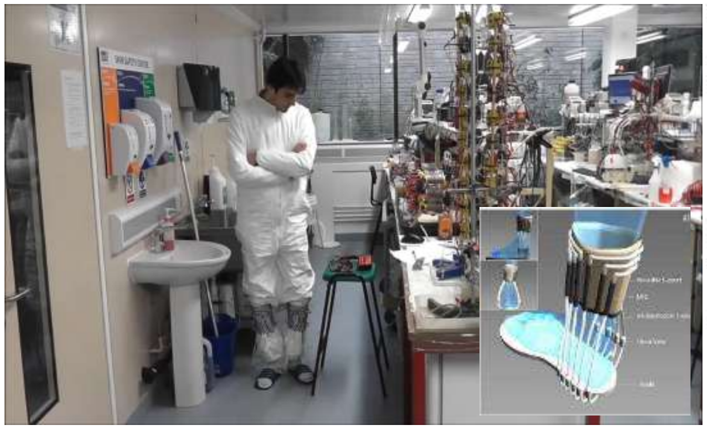


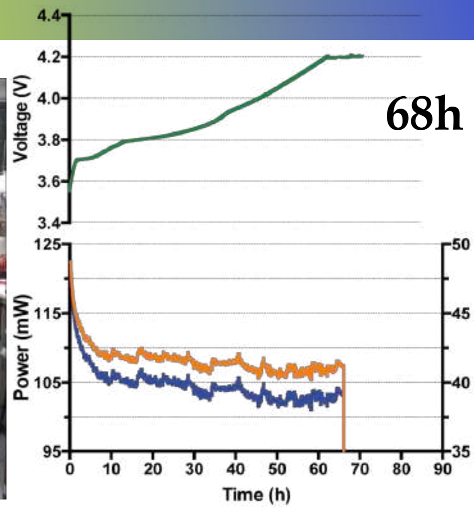
25.7kJ



From *mW*

To *Watts*

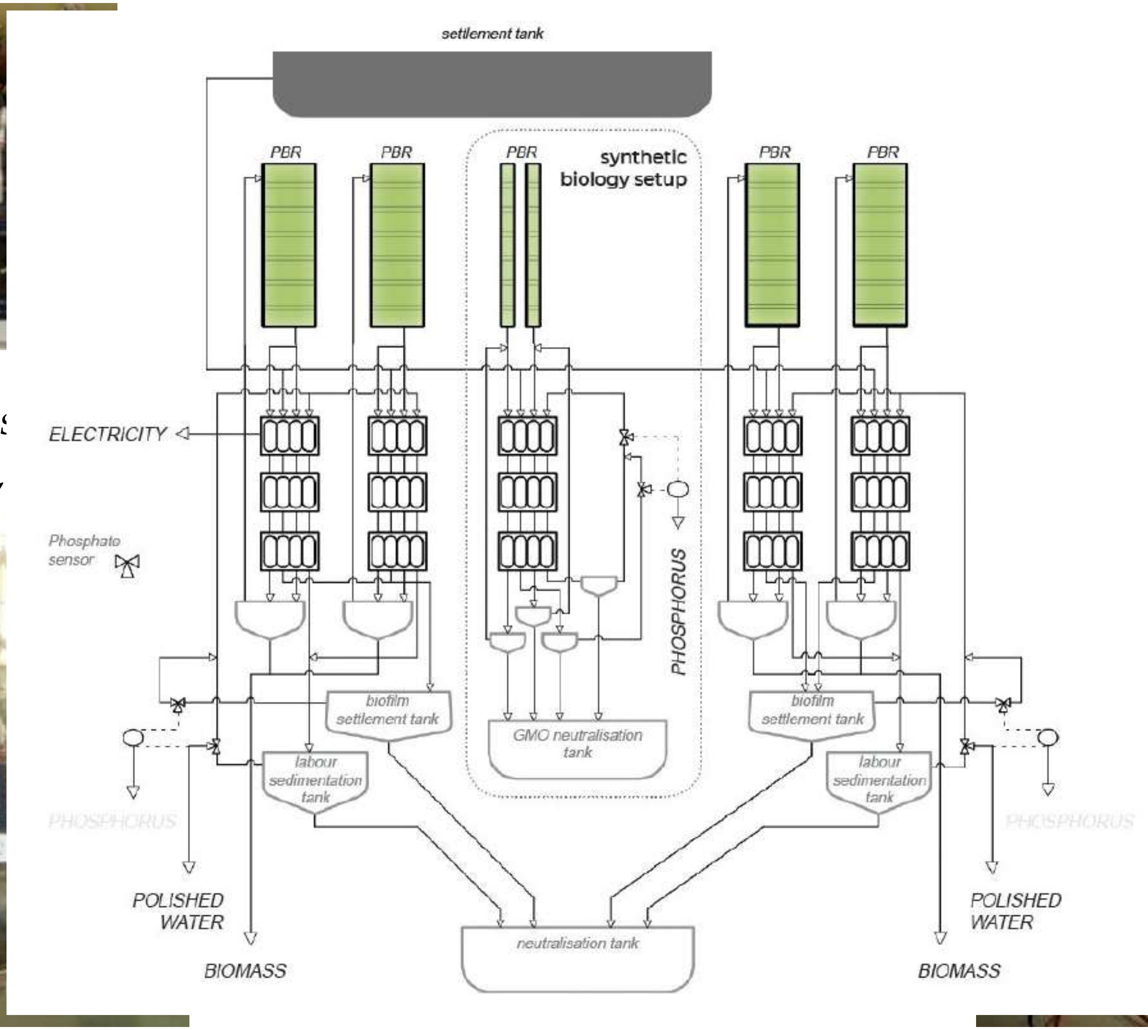


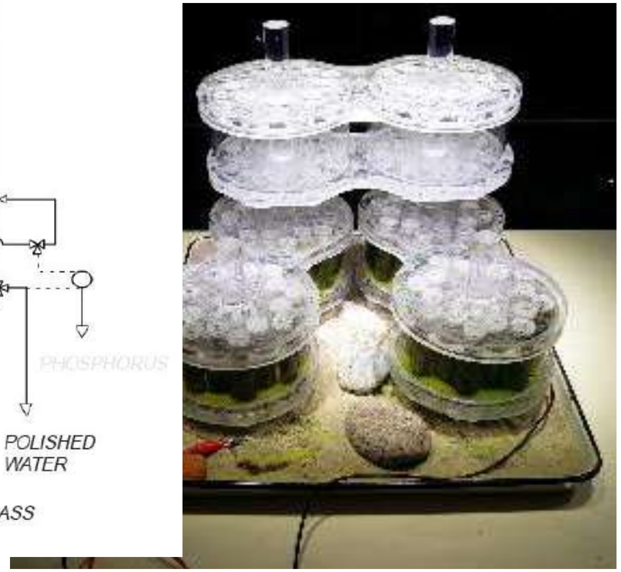


68h

Living Architecture (EU-H2020-FETOPEN grant no. 686585)

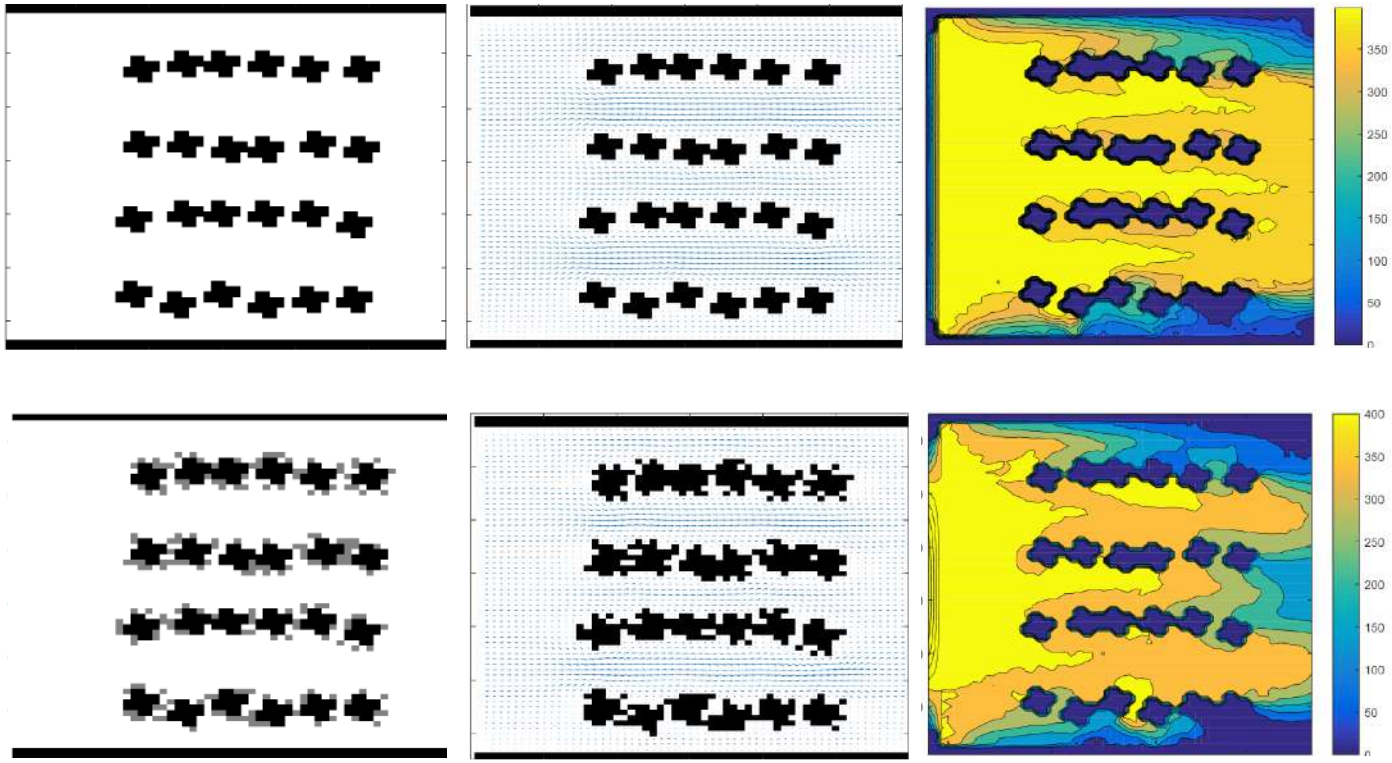
“Living brick” demons
at the Building Centre,

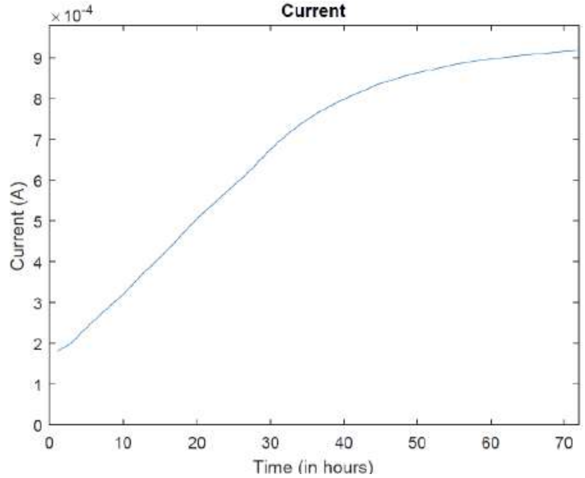


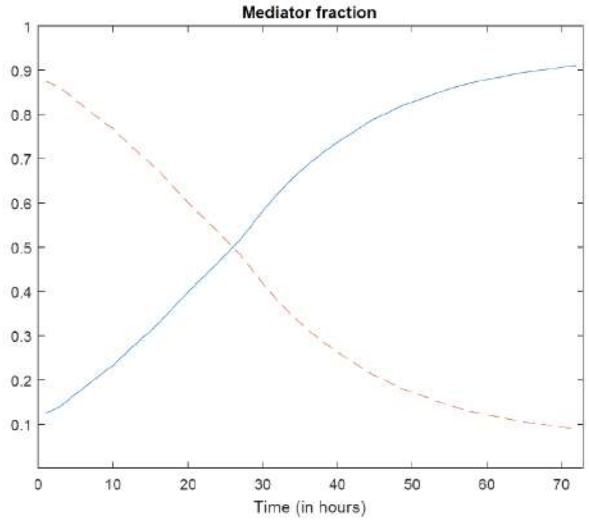


Computer modelling with reactor array

Results of modelling







Modelling microbial fuel cells using Lattice Boltzmann methods. 2018. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*.

Artificial Neural Networks

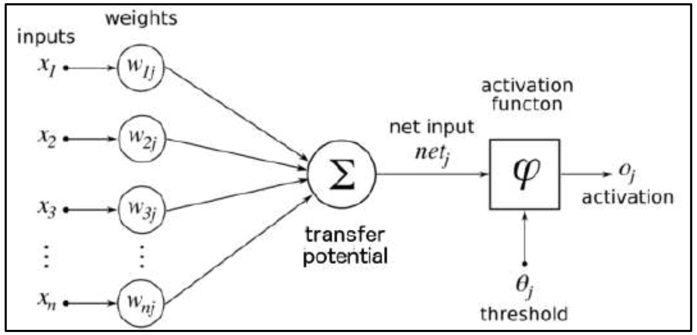
- Critical parameters, e.g. biofilm thickness, biofilm composition and substrate utilization rate are difficult to control/measure *in situ*

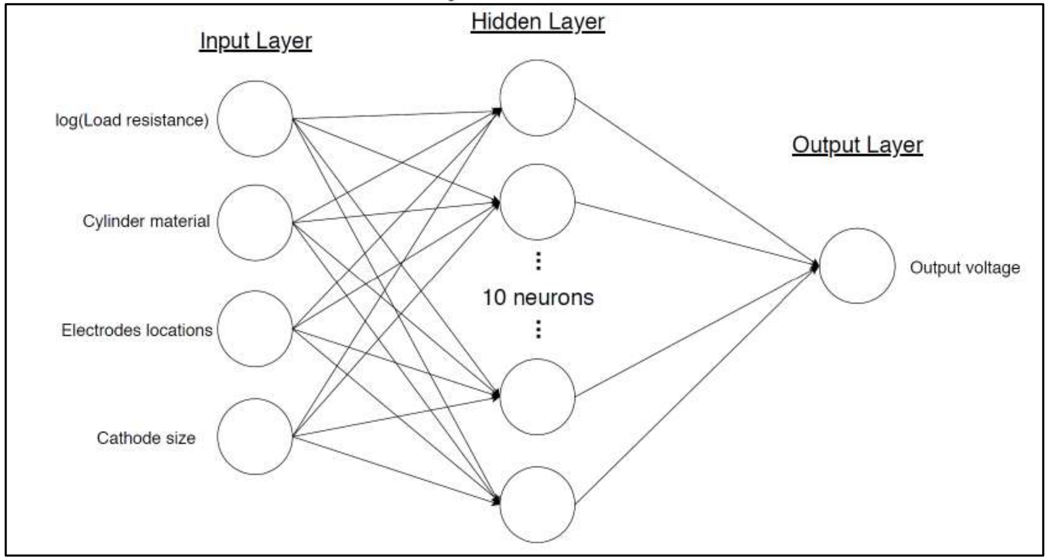
- These difficulties can be overcome by modelling bioreactors with machine learning (ML) techniques, whereby only system inputs and outputs are required (system governing rules are run by algorithm)

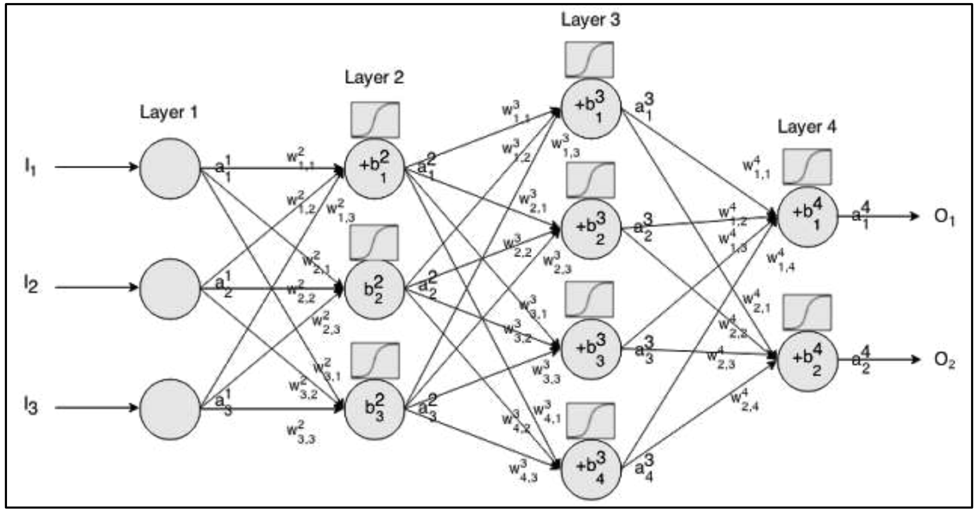
- Artificial Neural Networks (ANNs) have been utilized to tackle a diverse range of problems

- ANNs have a parallel distributed structure and an ability to learn and produce good estimated outputs for inputs that were not processed during the learning function of the network

Artificial Neural Networks







A. Tardas *et al.* J Biotechnol Pharm Res 3 (2012) 62–68.
A. Tardast *et al.* Fuel 117 (2014) 697–703.
A. Garg *et al.* Expert Syst Appl 41 (2014) 1389–1399.
M. Esfandyari *et al.* J Taiwan Inst Chem E 58 (2016) 84–91.
A. J. Jaeel *et al.* J. Electroanal Chem 767 (2016) 56–62.
Z. Z. Ismail *et al.* Biofuels (2017) 1–9.
K. L. Lesnik *et al.* Environ Sci Technol 51 (2017) 10881–10892.
Y. Sewsynker *et al.* Biotechnol Biotec Eq 29 (2015) 1208–1215.
A. de Rámon-Férnandez *et al*. Appl Energy (2019) 251 113321

Artificial Neural Networks

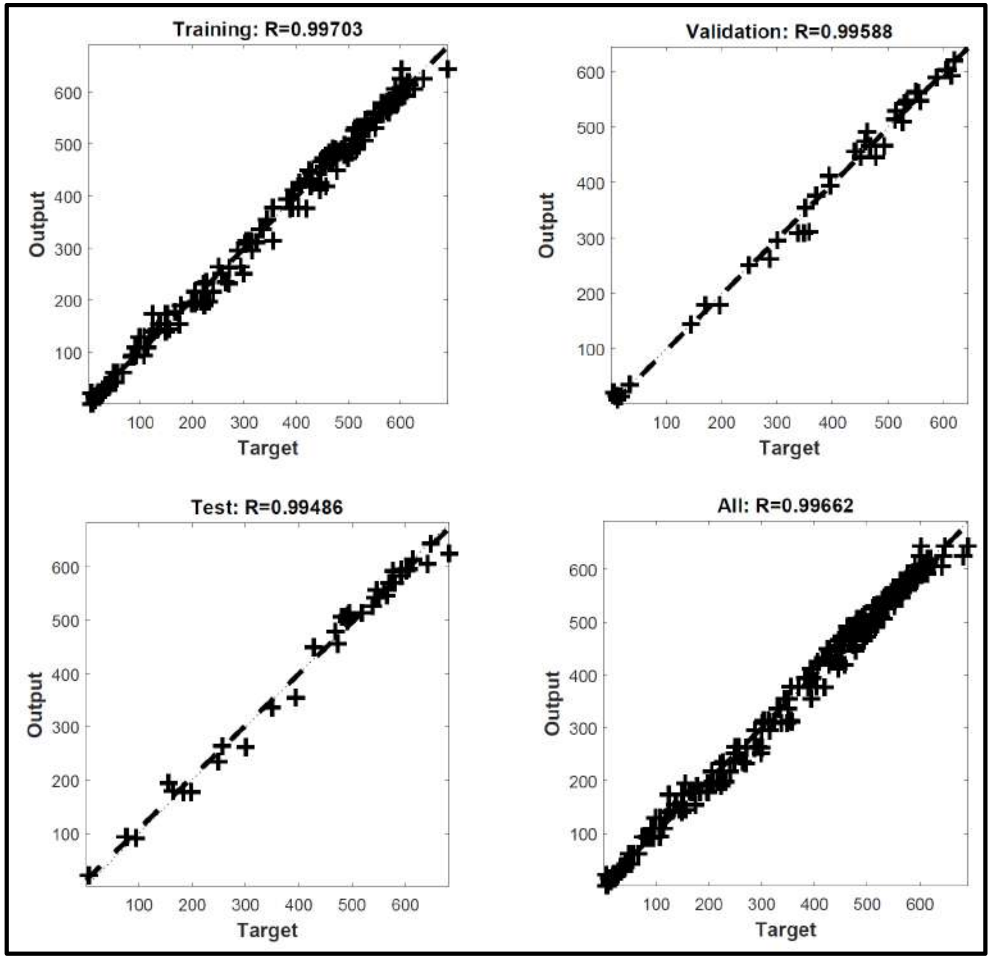
Training and Testing the ANN

For the training procedure, the data set was randomly divided in

- 70% (184 samples) for the training set,
- 15% (40 samples) for the validation set and
- 15% (40 samples) for the test set.

The majority of the value points are adequately close to the 45 degrees line, which indicates a perfect fit of the modelled data to the real data.

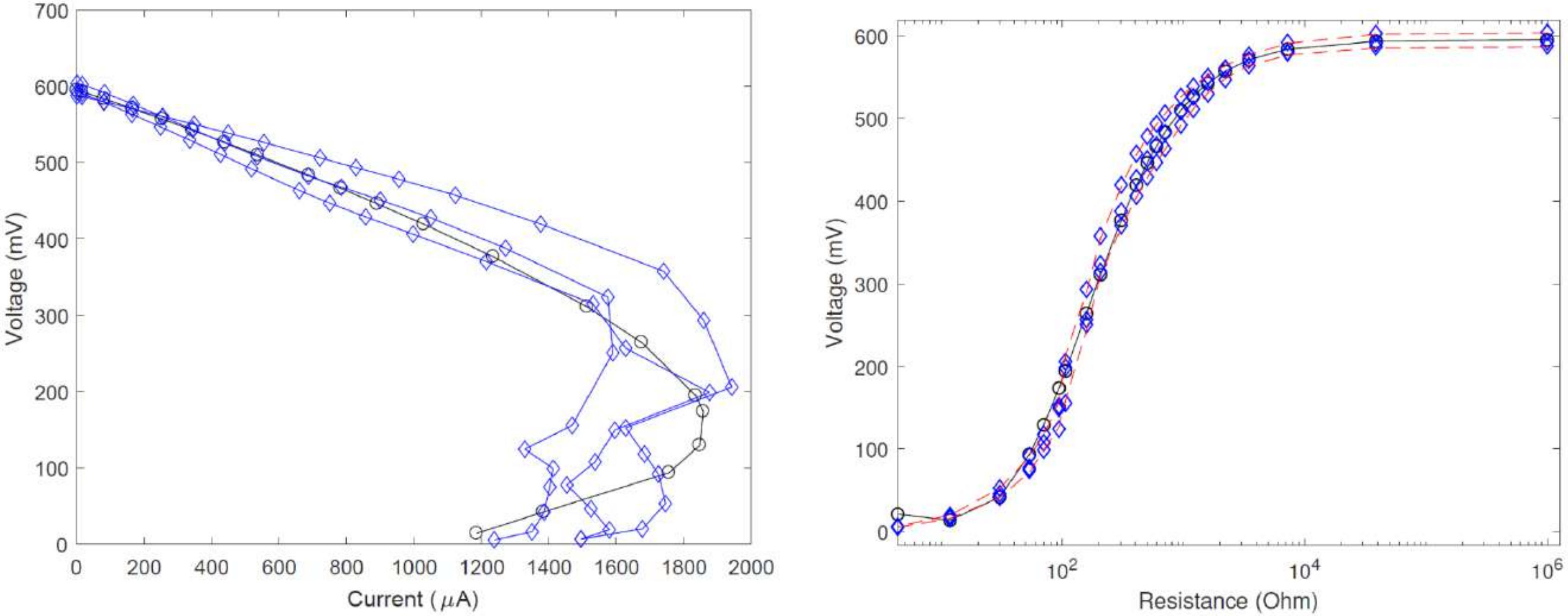
The correlation coefficient equal to 1 represents a perfect model.



Artificial Neural Networks

Validation of the ANN model

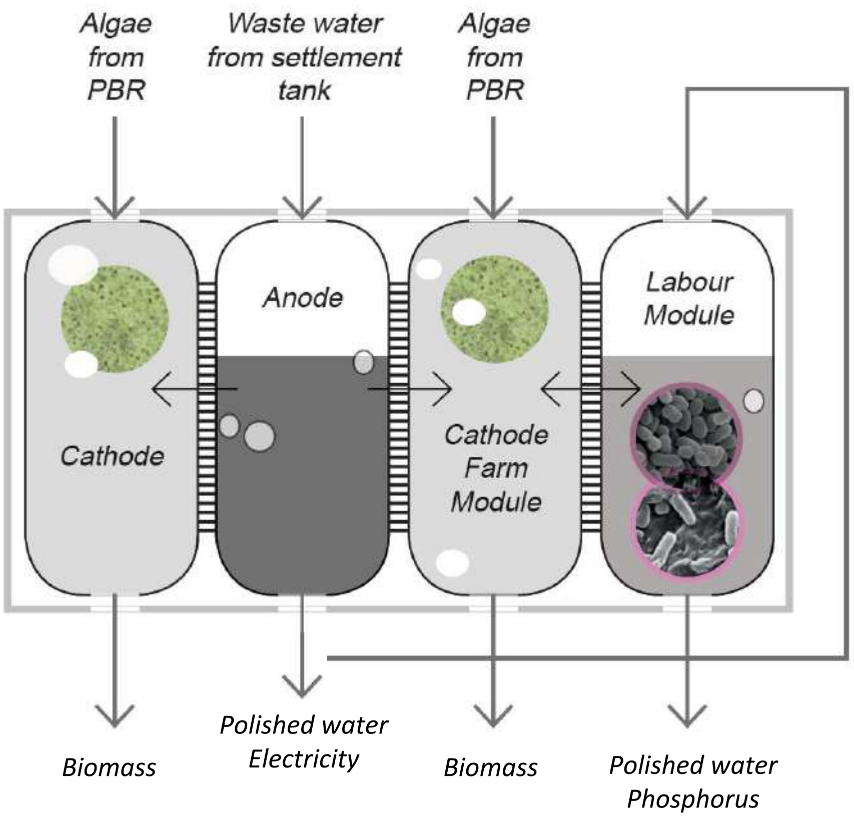
After the network was trained and tested, it was used to produce data (here voltage), for B_Cout type of MFCs.



Artificial neural network simulating microbial fuel cells with different membrane materials and electrode configurations, 2019. *Journal of Power Sources*, **436**:226832

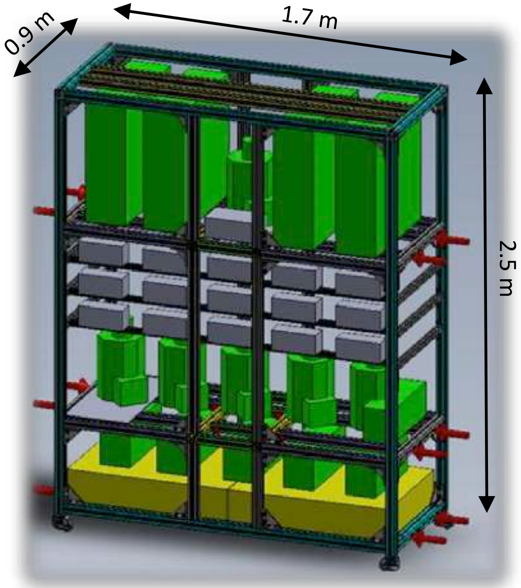
"Living brick" design and fabrication

Bioreactor wall building block configuration

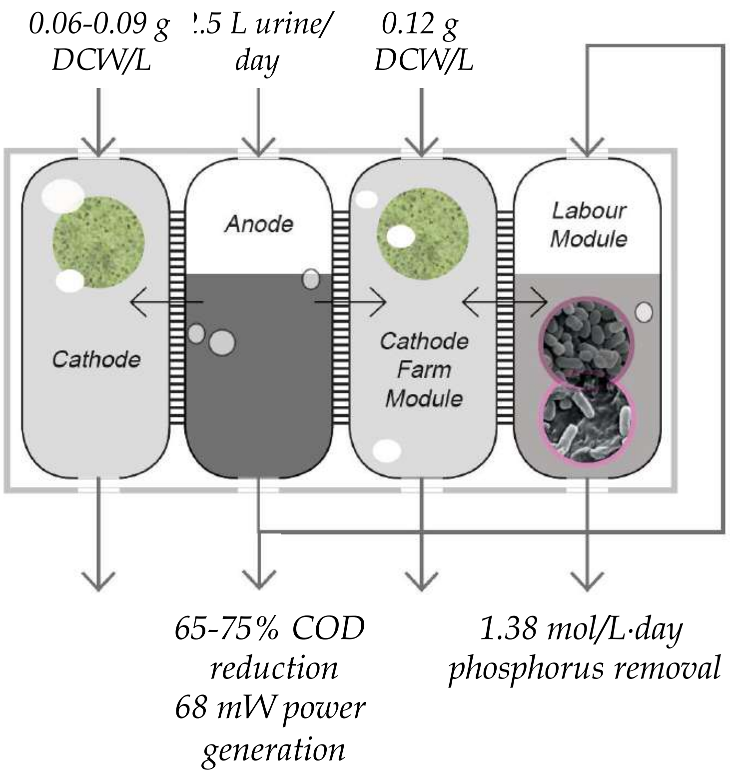


Living Bioreactor Wall

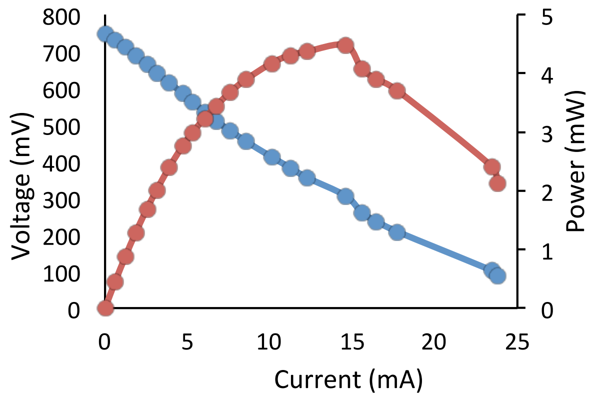
Living Architecture bioreactor wall installation



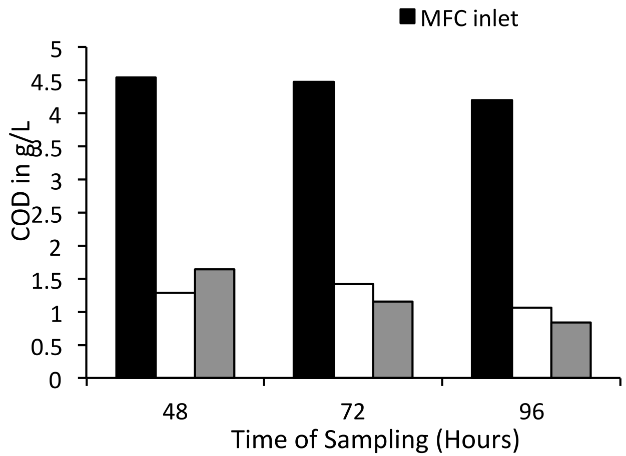
Living Bioreactor Wall



4.5 ± 0.6 mW/brick on average
(maximum of 5.4 mW/brick)



Treatment efficiency 65 – 75 %
(HRT of 14.4 hours)



Living Bioreactor Wall

http://eprints.uwe.ac.uk/id/eprint/41254

Pee Power® field trials: Uganda and Kenya

Social science (*WSN, UWE*):

- 86% of pupils felt safer going to toilet at night (from male attackers & animals/insects)
- 98% liked the idea of using urine to create electricity
- 83% would like Pee Power rolled-out to their village
- Pee Power encourages girls to go to the toilet at night
- Pee Power is seen as a means of lowering cost of electricity at the school
- Many pupils are interested in science and enjoyed learning about the technology

Acknowledgments

Professor Chris Melhuish
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BBiC Bristol BioEnergy Centre

EPSRC Engineering and Physical Sciences Research Council

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Newcastle University

The Thriplow Trust

scion FORESTS | PRODUCTS | INNOVATION

IT University of Copenhagen

OXFAM

RSE Ricerca Sistema Energetico

Roca

LIQUIFER SYSTEMS GROUP

UNIVERSITY OF TRENTO - Italy

University of Glasgow

Innovate UK Technology Strategy Board

California Institute of Technology 1891

SEVENTH FRAMEWORK PROGRAMME

CogSys Cognitive Systems

GREAT WESTERN RESEARCH

KIT Karlsruhe Institute of Technology

Dunster House

CSIC CIB

Information Society

Wessex Water a YTL company

THE BIOROBOTICS INSTITUTE Scuola Superiore Sant'Anna

Duke UNIVERSITY

WhiffAway™ waterless technologies

KOHLER®

The Leverhulme Trust

THE UNIVERSITY of NEW MEXICO New Mexico's Flagship University

CIBIO

EXPLORA BIOTECH pioneering nature

MÉXICO GOBIERNO DE LA REPÚBLICA

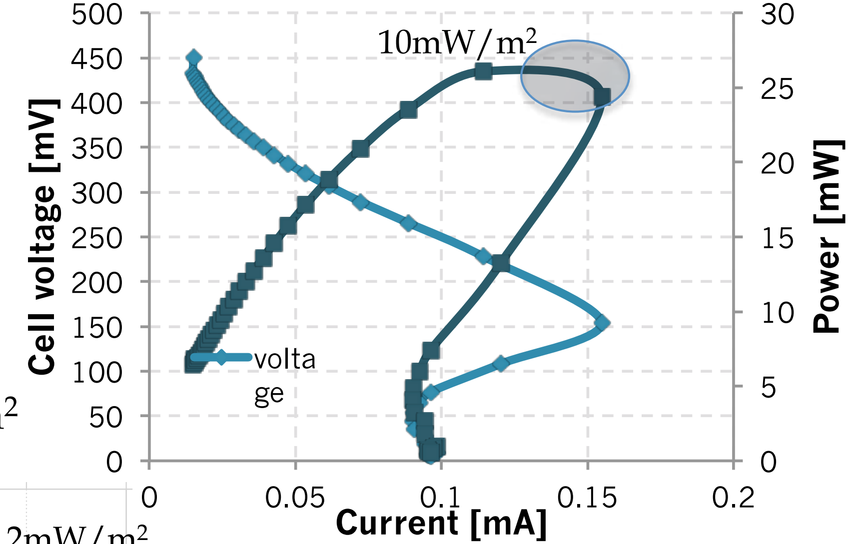
CONACYT Consejo Nacional de Ciencia y Tecnología

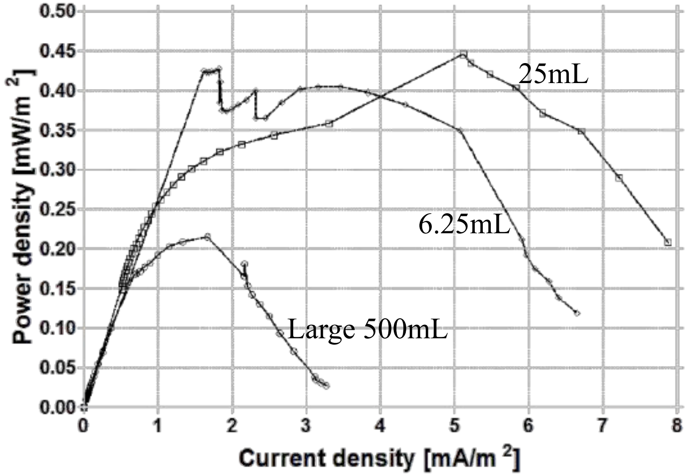
MFC scale-up investigation: big vs. small

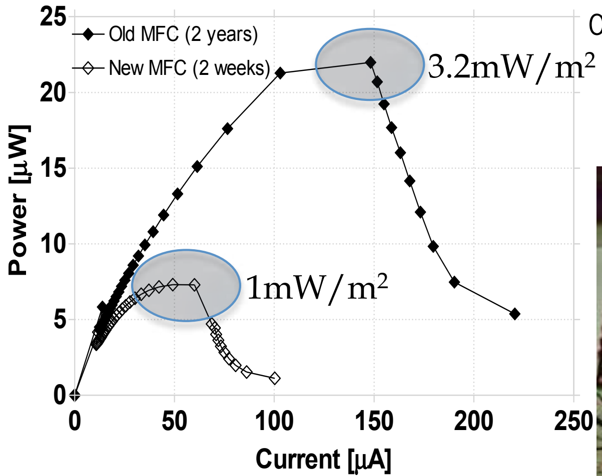
Volume = 50mL
Electrode = 270cm^2

Volume = 6.25mL
Electrode = 67.5cm^2

Volume = 1mL
Electrode = 28cm^2







Int J Energy Res **32(13):** pp 1228-1240; *Bioelectrochemistry*, **78(1)**:44–50

EVOBLISS

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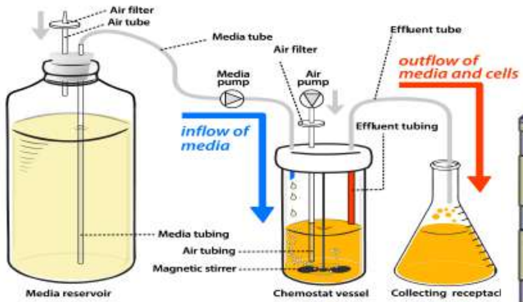
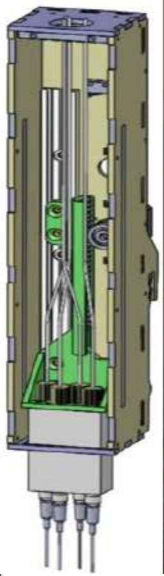
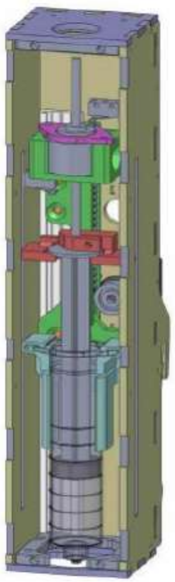
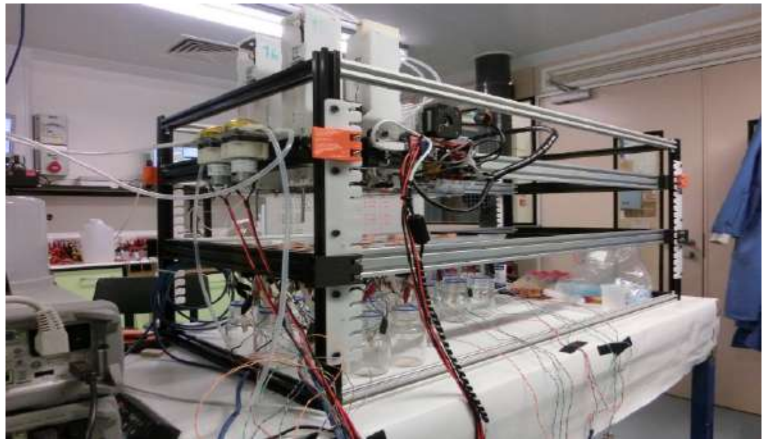
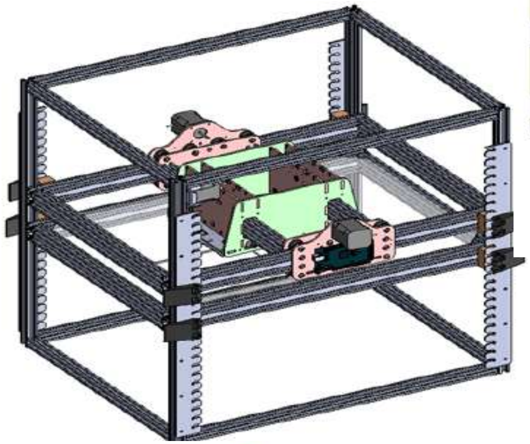
EU FP-7 EVLIT grant no. 611640











IT University of Copenhagen

University of Glasgow

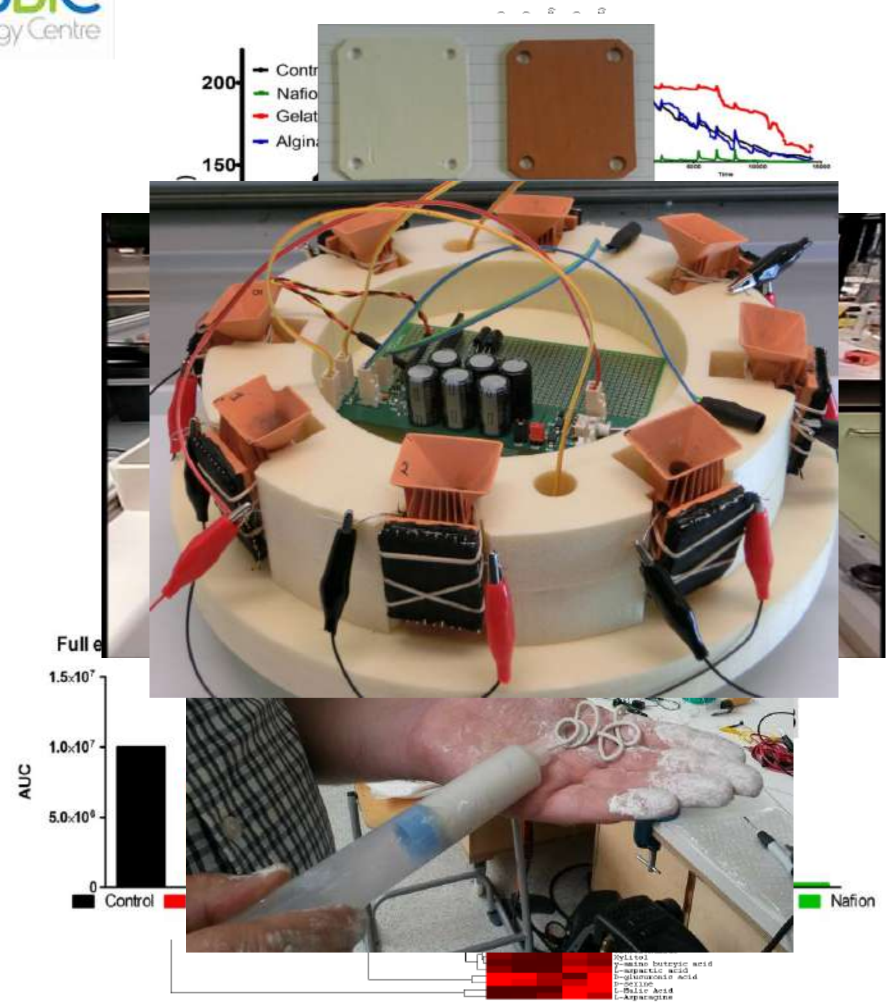
KIT Karlsruhe Institute of Technology

UNIVERSITY OF TRENTO - Italy

UWE Bristol University of the West of England

Project objectives:

- Inoculum investigation
  - Phenotypic analysis
- Substrate investigation
  - Liquid, gel-like - extrudable
- Substratum investigation
  - Chassis, membrane - extrudab
- Electrode investigation
  - Conductive extrudable pastes
- EcoBot-II evaluation



Biomimetic & Biohybrid Systems, Springer, ISBN: 97836443298018 (Living Machines 2017)

Computer modelling with reactor array

Living Architecture

BBiC Bristol BioEnergy Centre

Motivation:

- complexity of MFCs
- number of parameters that affect their outputs
- costs in time and money needed to perform laboratory experiments

Model reactor array

Detailed model of a **single** reactor

- bio-chemical mass-kinetics
- spatial-temporal dynamics of the reagents
- metabolites transfer inside a reactor
- long-duration of the whole system

Factors of limitations on performance:

- microbial activity,
- ohmic losses,
- mass transfer on the electrode surfaces,
- non-optimised electrode architectures and
- transfer potential through the PEM

1. Continuous dynamics in continuous space are converted to discrete space changes
2. Transitional periods are conducted using cellular nonlinear networks (CNN)

Computer modelling with reactor array

Primary goal to produce an accurate model of bio-electrochemical processes that govern Microbial Fuel Cells (MFCs) and map their behaviour according to key parameters

The geometry of the electrodes is amongst key parameters determining efficiency of MFCs due to the formation of a biofilm of anodophilic bacteria on the anode electrode

Simulate MFC electro-chemical processes by considering electrode geometry

Use Lattice Boltzmann to simulate fluid dynamics and the advection-diffusion phenomena in the anode

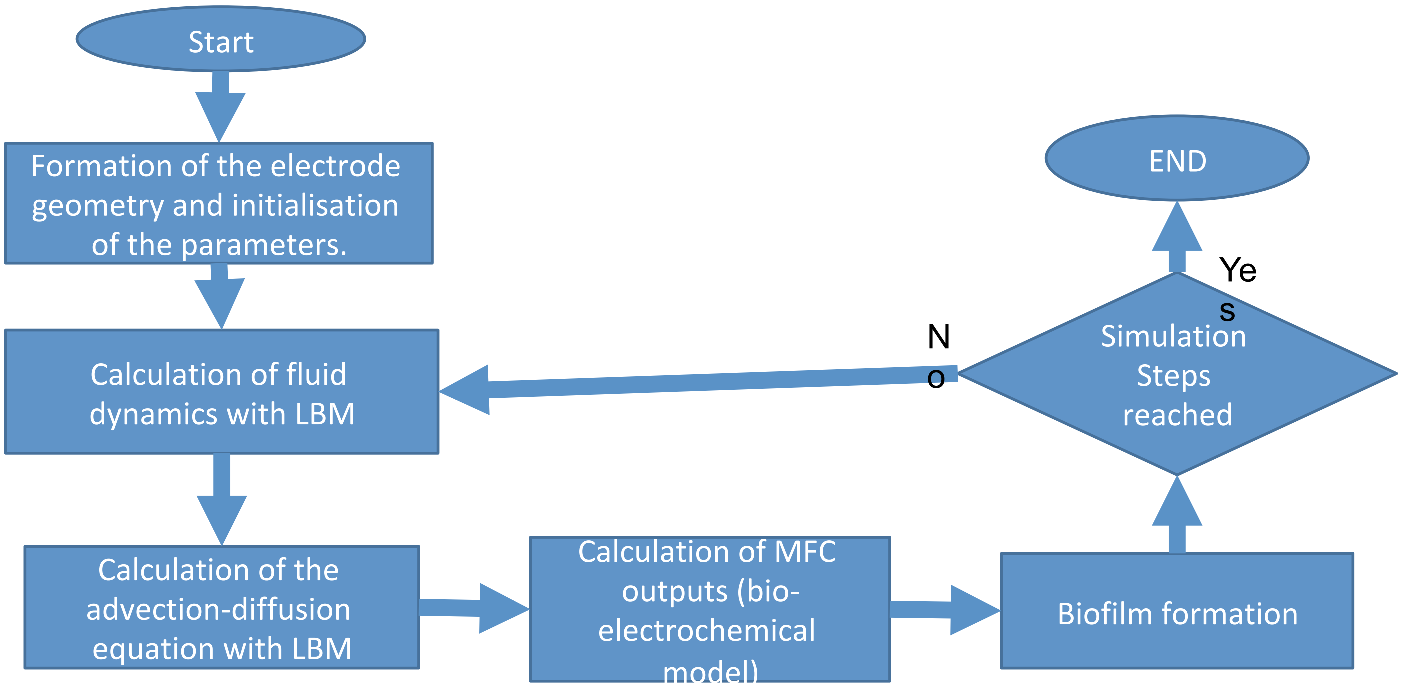
Model verified by voltage and current data of a real MFC tested in the lab under continuous flow

Living Architecture

Computer modeling with reactor array

WP 2

Structure of modelling



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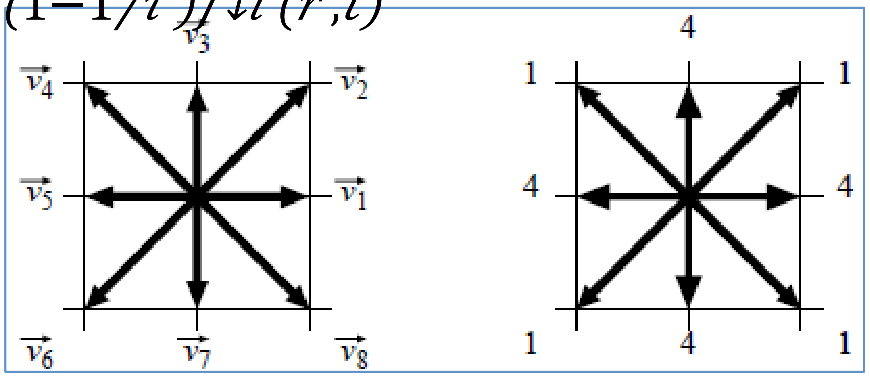
Lattice Boltzmann modelling

Averaging microdynamics before simulation implies quantities of interest are no longer boolean variables but probabilities of presence which are continuous variables ranging in the interval [0,1]

$$f_i(r+\Delta t\, u_i, t+\Delta t) = \frac{1}{\tau} f_i^{(0)}(r,t) + \left(1-\frac{1}{\tau}\right) f_i(r,t)$$

Considerably decreases the statistical noise and computational requirements

LB is widely used for simulating fluid flow and can compare with traditional numerical techniques of CFD



Operating at microscopic level allows intuitive generalizations to complex flow problems (i.e. flow in porous media).

Common example of LB fluid is the so-called D2Q9 model, defined in two dimensions (D2) with nine variables, or quantities per sites (Q9).

In a general $DdQ(z+1)$ LB fluid, the macroscopic quantities, such as the local density ρ or the velocity flow u are defined as:

$$\rho = \sum_{i=0}^{z} m_i f_i \qquad \rho u = \sum_{i=0}^{z} m_i f_i u_i$$

D. von der Schulenburg *et al*. AIChE Journal 55 (2) (2009) 494–504
S. Bottero *et al*. Biofouling 29 (9) (2013) 1069–1086
T. R. Pintelon *et al.* Biotechnol Bioeng 109 (4) (2012) 1031–1042
C. Picioreanu *et al*. App Environ Microbiol 70 (5) (2004) 3024–3040
T. L. Stewart *et al*. Biotechnol Bioeng 77 (5) (2002) 577–588.

Computer modelling with reactor array

Bio-electrochemical model of the MFC

After calculating the equilibrium of fluid dynamics and the concentration of the chemical species, the output of MFC is studied using the following equations:

$$M_{Total}=M_{red}+M_{ox}$$

$$M_{ox}(x,t+1)=M_{ox}(x,t)-Yq_{a}+\gamma I_{cell}/mF \; 1/V_{a}C^{bio}$$

Y is the mediator yield, γ is the mediator molar mass, m is the number of electrons during reduction of the intracellular mediator.

F is the Faraday constant, V_a is the anode compartment volume, C^{bio} is the concentration of biomass, I_{cell} is the total current produced and q_a is the consumption rate of the substrate.

The double Monod equation is used to determine the consumption rate of the substrate: $q_{a}=q_{max}\,C_{s}/(C_{s}+K_{s})\;M_{ox}/(M_{ox}+K_{mox}$

The concentration overpotential based on the Nerst equation is defined by: $\eta_{conc}=RT/F\ln(M_{To}$

The activation overpotential can be calculated by an approximation of the Butler-Volmer equation: $\eta_{act}=I_{cell}/A_{a}I_{0}\;R$

Computer modelling with reactor array

Bio-electrochemical model of the MFC

The mechanism for the transfer of electrons to the anode is assumed to incorporate the existence of an intracellular mediators and direct connection of cells to the electrode (by nanowires or by direct contact)

Kirchhoff's voltage law and Ohm's law can correlate the over-potential values, the resistance values and the produced current

$$I_{cell} = (E_0 - n_{conc} - n_{act})/(R_{int} + R_{ext})$$

$$M_{red}/\varepsilon + M_{red}$$

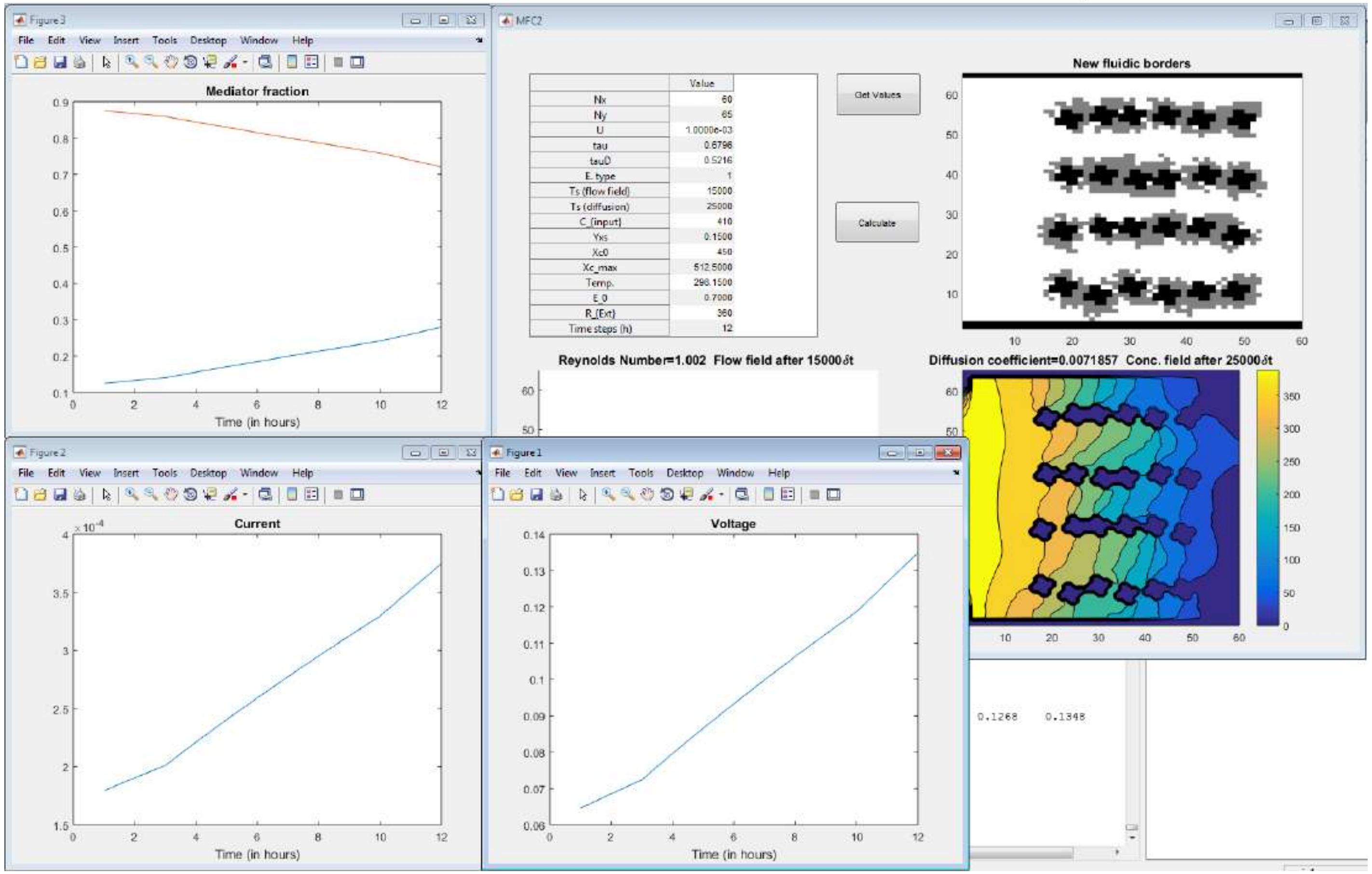
Ohm's law provides the voltage produced

$$V_{cell} = I_{cell} R_{tot} = I_{cell} (R_{int} + R_{ext})$$

Biofilm formation was used as an agent-based procedure to simulate the attachment and growth of biomass on the electrode. This was done by a random selection in each time step of a predefined number of lattice cells (k_{ata}) to change their biomass concentration to a predefined initial value ($C^{bio} = C^{bio}_0$)

Parameter	Description	Value
$X \times Y \times Z$	Anode compartment dimensions	$17 \times 60 \times 65mm$
$X' \times Y' \times Z'$	Anode electrode dimensions	$17 \times 48 \times 65mm$
$L_X \times L_Y$	Model lattice dimensions	60×65
ϕ	Electrode porosity	0.874
V	Fluid input velocity	$1.758 \cdot 10^{-2}mm/s$
v	Kinematic viscosity	$1.004mm^2/s$
τ	Dimensionless relaxation time (LBM)	0.6706
D	Diffusion coefficient	$0.0012mm^2/s$
τ_D	Dimensionless relaxation time (LBM)	0.5036
C_s^{in}	Input substrate concentration	$410\ mg\ substrate\ /\ L$
$Mtotal$	Total amount of intracellular mediator	$0.05\ \frac{mg\ mediator}{mg\ biomass}$
Y	Intracellular mediator yield	$0.5687\ \frac{mg\ mediator}{mg\ substrate}$
γ	Mediator molar mass	$663400\ \frac{mg\ mediator}{mol\ mediator}$
m	Electrons provided during reduction	$2\ e$
q_{max}	Maximum consumption rate	$8.48\ \frac{mg\ substrate}{mg\ biomass \cdot day}$
K_S	Half saturation constant for substrate	$20\ (mg\ substrate\ /\ L)$
K_{Mox}	Half saturation constant for oxidised mediator	$0.02 \times Mtotal\ (mg\ mediator/L)$
I_0	Exchange current density	$0.001\ A/m^2$
E_0	Open circuit voltage	$0.7\ V$
R_{ext}	External ohmic resistance (load)	$360\ \Omega$
R_{int}	Internal ohmic resistance	$360\ \Omega$
k_{ata}	Predefined number of cells for attachment	200
C_0^{bio}	Initial biomass concentration	$450mg\ biomass\ /\ L$
C_{max}^{bio}	Threshold biomass concentration	$512.5\ mg\ biomass\ /\ L$
fr_{spr}	Fraction of the biomass spreading	40%

Computer modelling with reactor array



Computer modeling with reactor array

WP 2

Future work

Flow dynamics and the advection-diffusion phenomena of chemicals are modelled in short time intervals (seconds and minutes). Thus, the model can be utilised in predicting transitions of the behaviour of a MFC from one state to another in this time span.

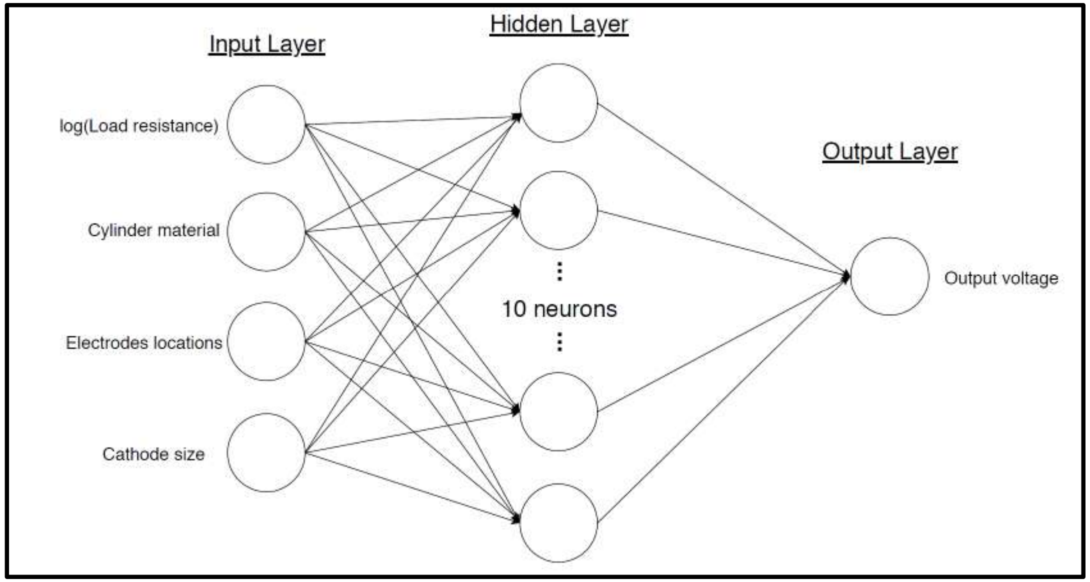
The model can include analysis of the effect of specified geometries and micro-structures on the development of biofilms in a MFC and its electrical and chemical outputs, e.g. geometries based data from X-ray tomographic microscopy.

More work can be focused towards the study of the permeability of biofilms and communication between cells in the matrix.

While, in the simulated experiments the total concentration of the intracellular mediator is regarded as constant and analogous to the biomass concentration, in reality, fractions of oxidised and reduced forms of the mediator can vary.

An application of a ANN for MFCs

- A forward-fed and back-propagation ANN with topology of 4-10-1 neurons was developed.
- The four input neurons represent the four input parameters and the output neuron, the voltage of the MFC.
- The data set that was produced by laboratory experiments and comprises 264 samples (4 types of MFCs X 3 lab instances X 22 values of load resistances).



Artificial Neural Networks

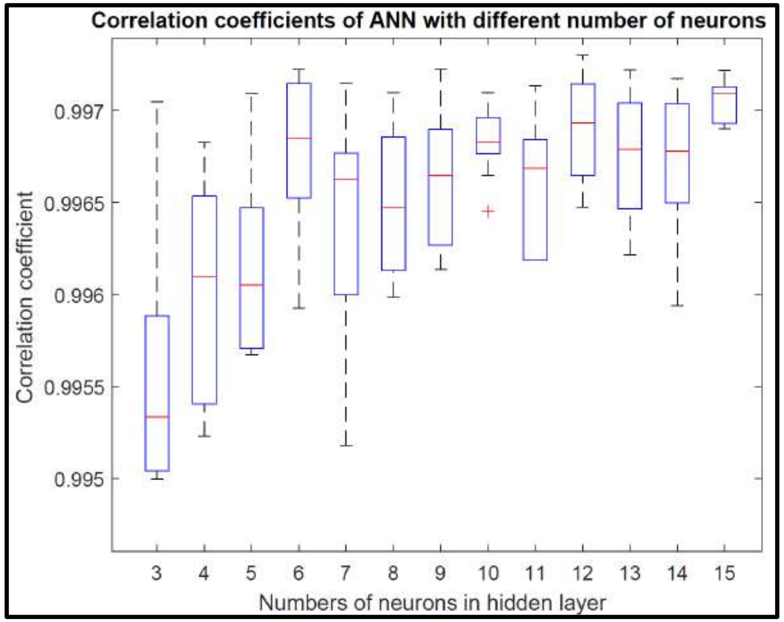
Why 10 hidden neurons?

Different topologies of ANNs were tested with the neurons varying from 3 to 15; to study the effect that the number of neurons in the hidden layer has onto the accuracy of the network.

Each topology was tested for 10 runs to alleviate a possible impact that the initial random fragmentation of the data set has on the performance of the network.

Distribution of correlation coefficients of the ANNs outputs is shown on the right.

The topologies providing the higher performance and being less affected by the initial random fragmentation of the data set are with 10 and 15 neurons.



Computer modelling with reactor array

Summary

Using ANNs to predict MFC outputs is becoming a popular method due to their fast implementation and their dissociation of the need for detailed knowledge of the underlying rules.

On the contrary, rule-based models involve developing an ensemble of highly accurate formulas that describe all processes (physical, biological and electro-chemical) that occur within the system.

Developing this type of ANN would be a first step towards designing an efficient fast responding controller for MFCs. As MFCs are susceptible to changes in the association of voltage and current, conventional maximum power point tracking algorithms are inadequate, particularly when voltage overshoot is observed. Thus, smarter techniques of energy harvesting control are required for MFCs.

The proposed ANN model was able to accurately simulate the overshoot phenomenon, which is an indication of suboptimal system performance, especially in the higher current ranges, and is an indication of ionic depletion in the anode.

Computer modeling with reactor array
WP 2

Future work

The element of time is going to be added in the ANN, in order to predict the outputs of a MFC as a time series.

Dynamic ANNs with feedback will be used, that can be transformed between open-loop and closed-loop modes. Closed-loop networks make multistep predictions. In other words they continue to predict when external feedback is missing, by using internal feedback.

One application for this is making time-series predictions of a bioreactor, where the last value is usually known (open-loop prediction) or when the reading is not available, or known to be erroneous (closed-loop prediction). The predictions can alternate between open-loop and closed-loop form, depending on the availability of the last step's reading.

Computer modeling with reactor array
WP 2

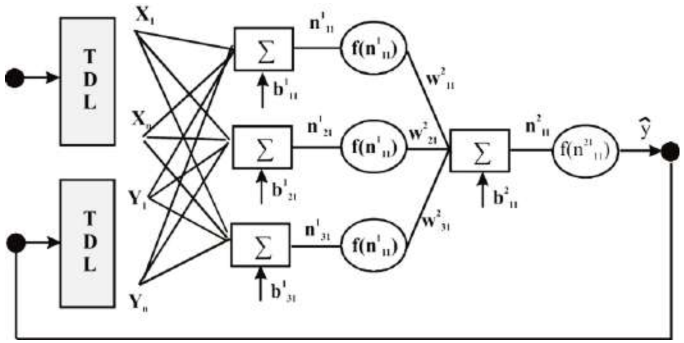
Future work

The prediction of a time series of the system's output is achieved with a dynamic neural network.

Namely, a nonlinear autoregressive network with exogenous inputs (NARX) was employed to predict the voltage output of an MFC brick, given its previous outputs and the feeding volumes of urine.

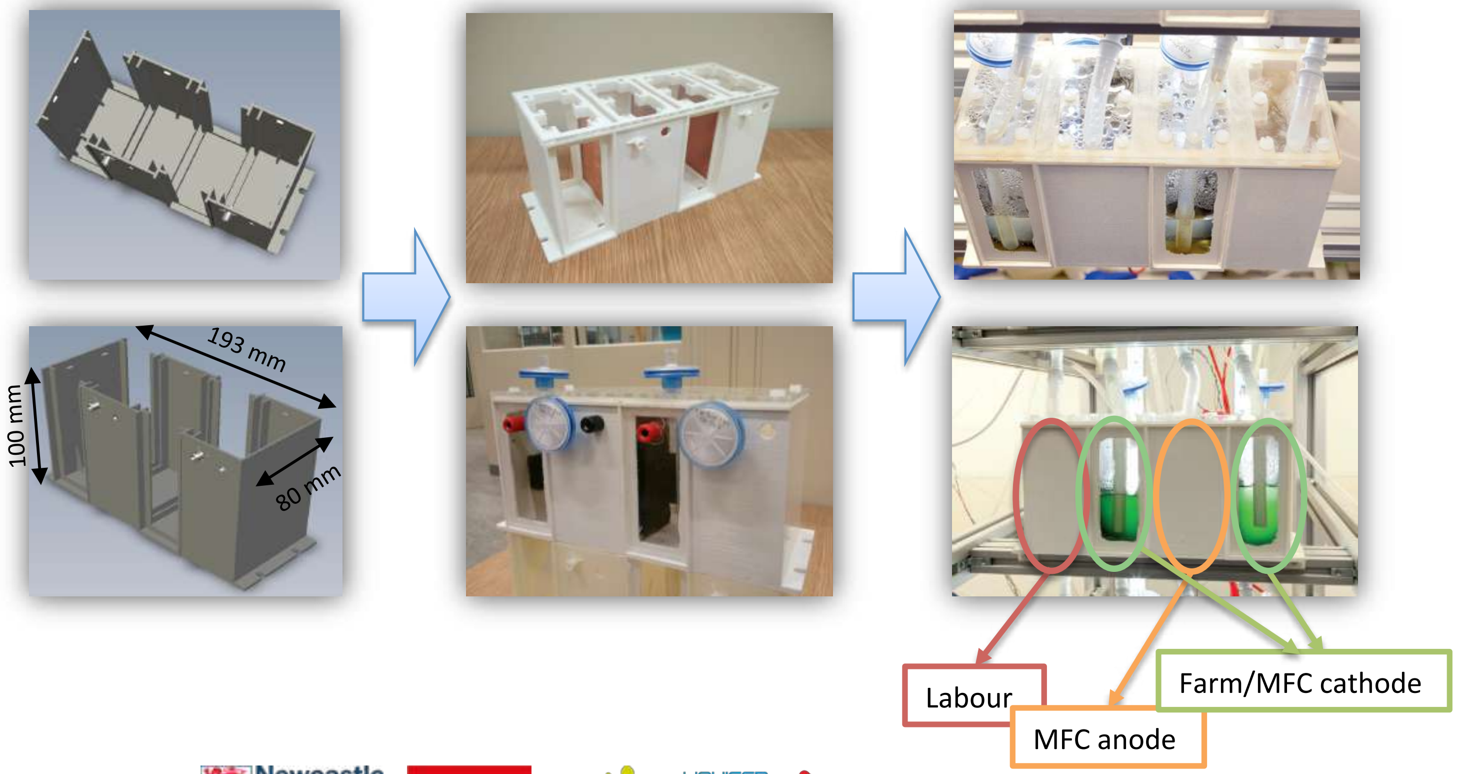
A NARX network can be detailed as:

$$y(t)=f(y(t-1),\ldots,y(t-d),x(t-1),\ldots,x(t-d))$$



"Living brick" design and fabrication

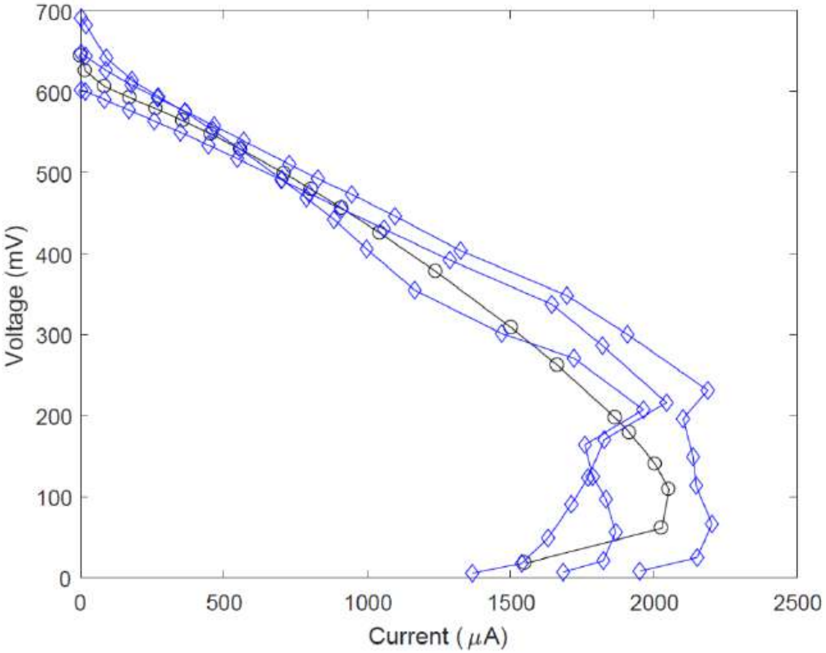
Bioreactor wall building blocks

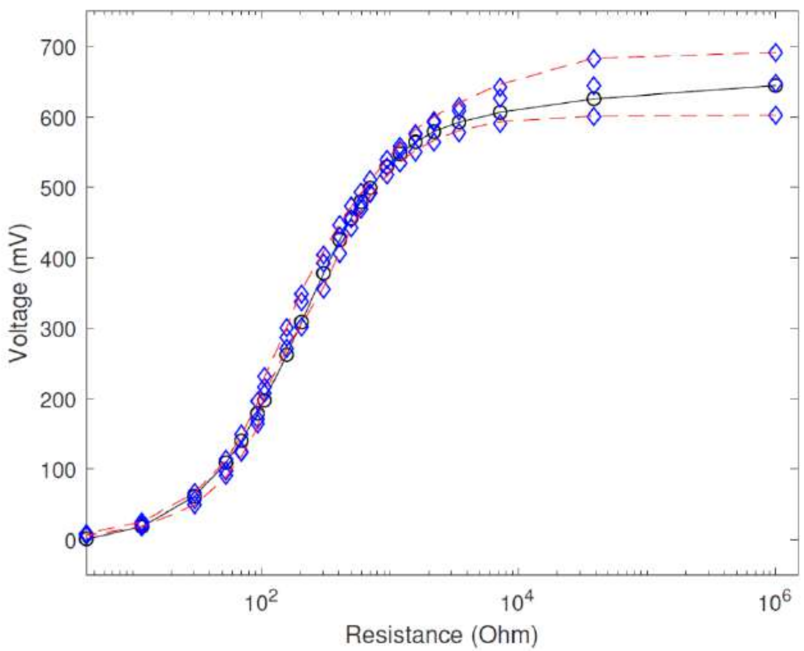


Artificial Neural Networks

Validation of the ANN model

After the network was trained and tested, it was used to produce data (here voltage), for T_Cout type of MFCs.





Artificial neural network simulating microbial fuel cells with different membrane materials and electrode configurations, 2019. *Journal of Power Sources*, **436**:226832

Computer modeling with reactor array

WP 2

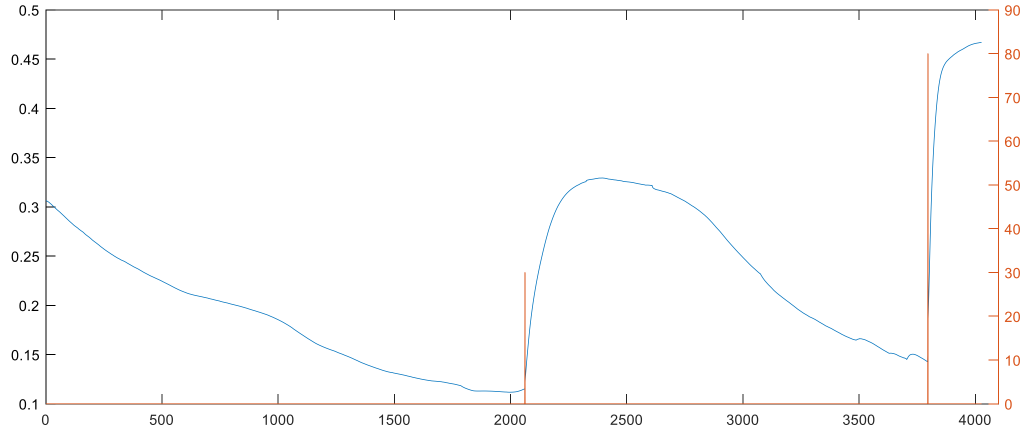
Future work

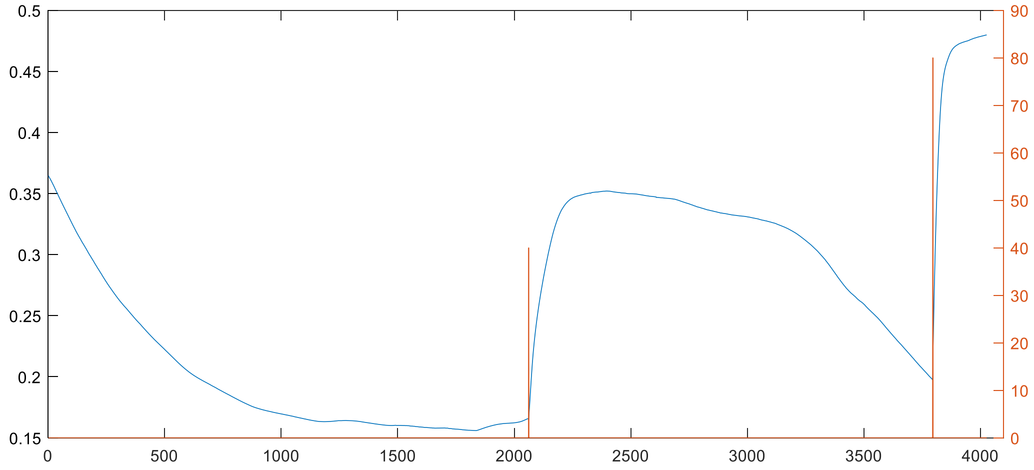
Outputs of two 3D printed boxes:

- Blue line:
Voltage output

- Orange line:
Feeding volume

Measurement interval:
5 minutes





Computer modeling with reactor array

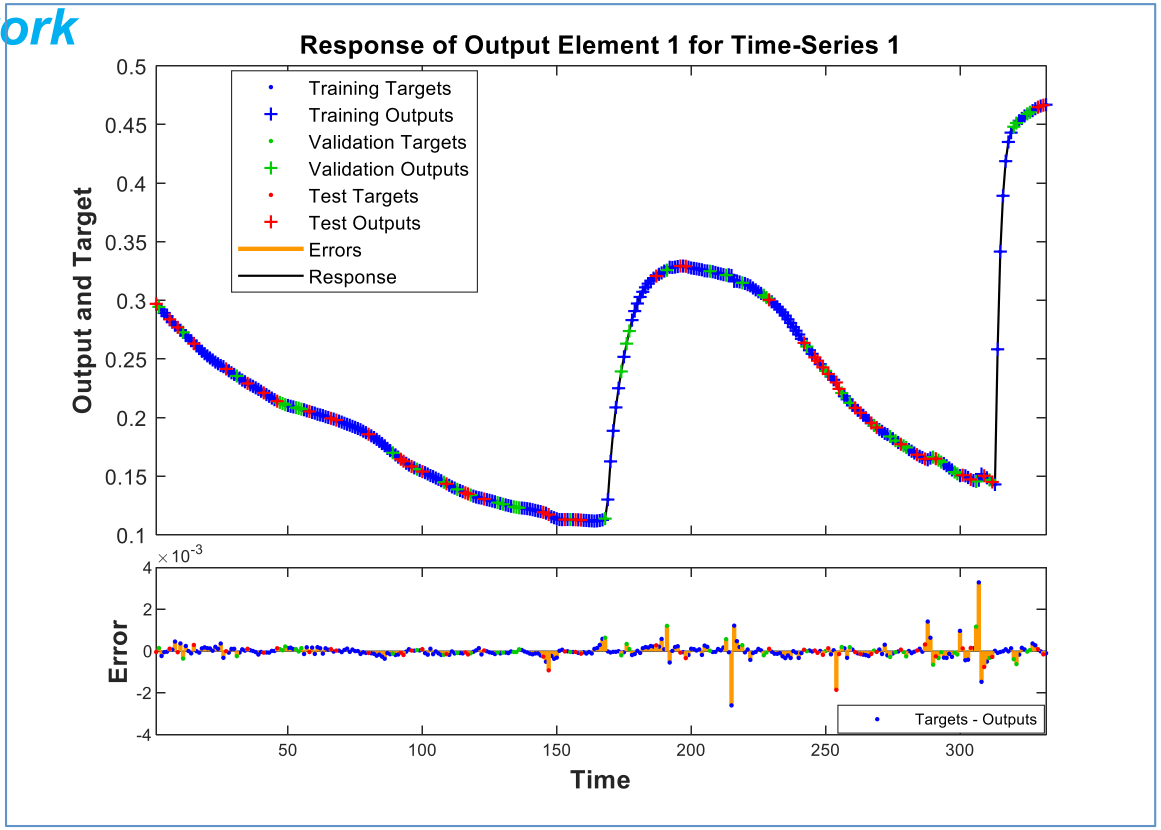
WP 2

Future work

Change the data set with intervals of one hour.

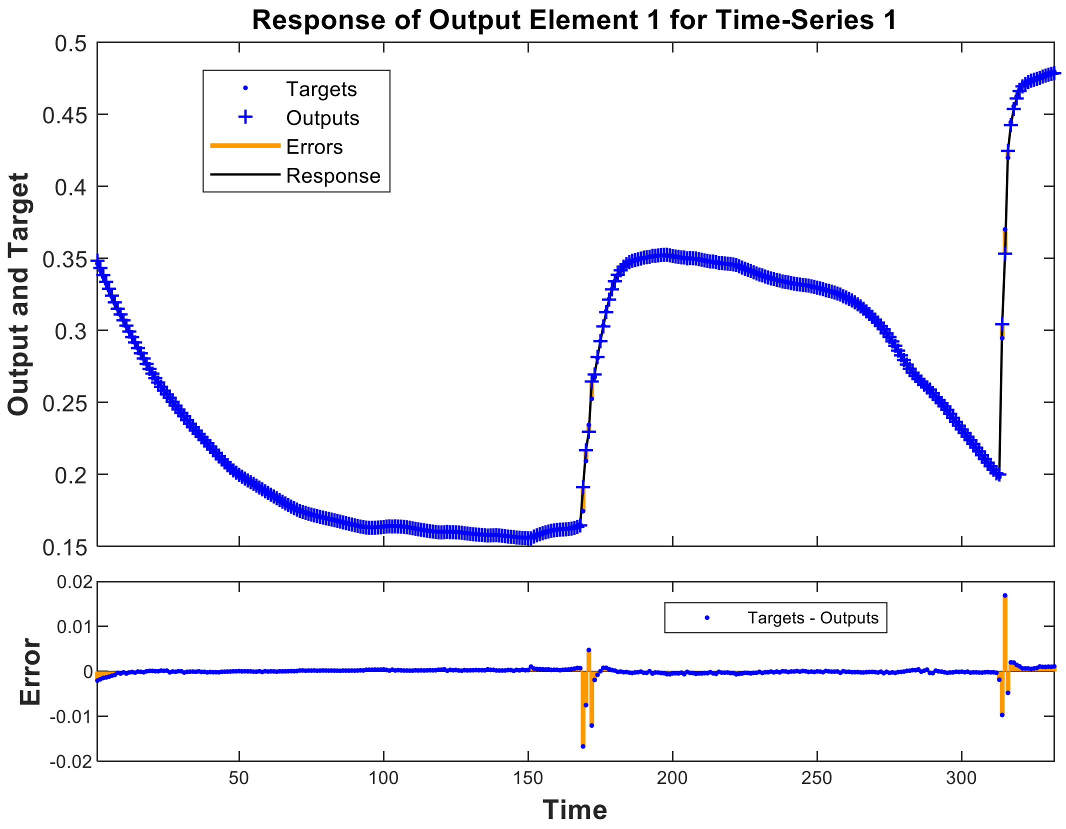
Train the ANN on the data set of the first brick and approximate the behavior of the second.

N. hidden neurons:
10
N. of delays:
4



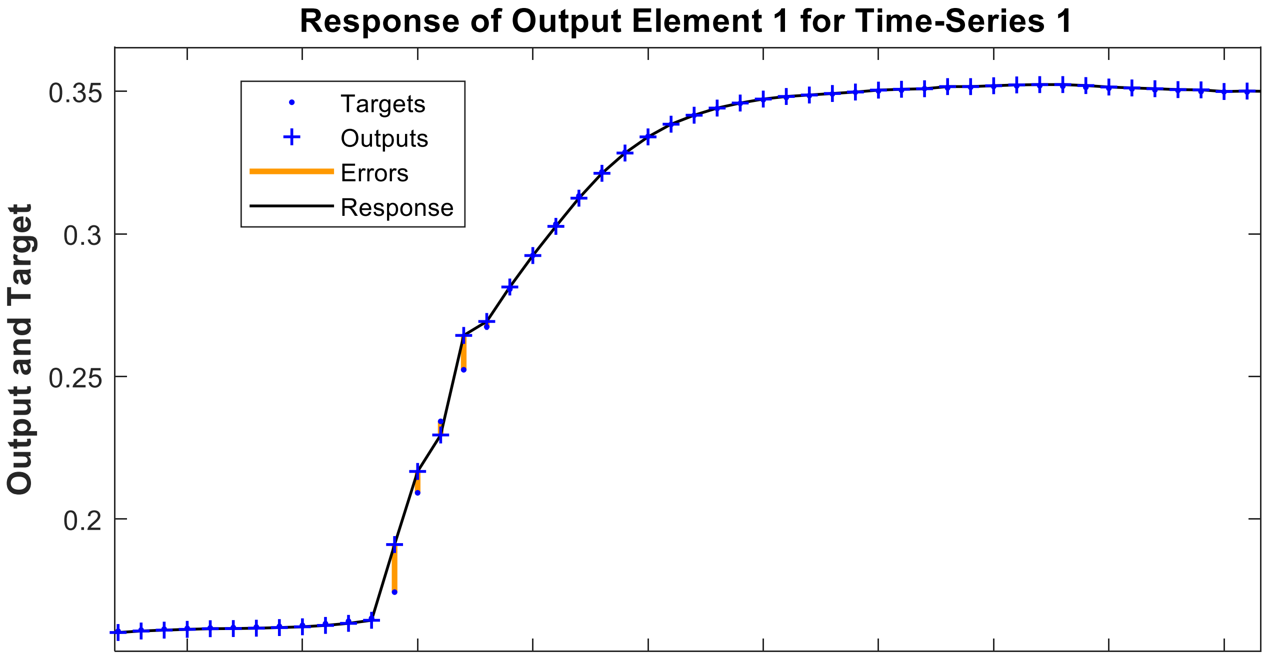
Computer modeling with reactor array
WP 2

Future work



Computer modeling with reactor array
WP 2

Future work



Publications:

[1] Tsompanas, M.A., Adamatzky, A., Ieropoulos, I., Phillips, N., Sirakoulis, G.C. and Greenman, J., 2018. **Modelling microbial fuel cells using Lattice Boltzmann methods**. IEEE/ACM transactions on computational biology and bioinformatics. (accepted – early access)

[2] Tsompanas, M.A., You, J., Wallis, L., Greenman, J. and Ieropoulos, I., 2019 "**Artificial neural network simulating microbial fuel cells with different membrane materials and electrode configurations.**", Journal of Power Sources. (under revision)

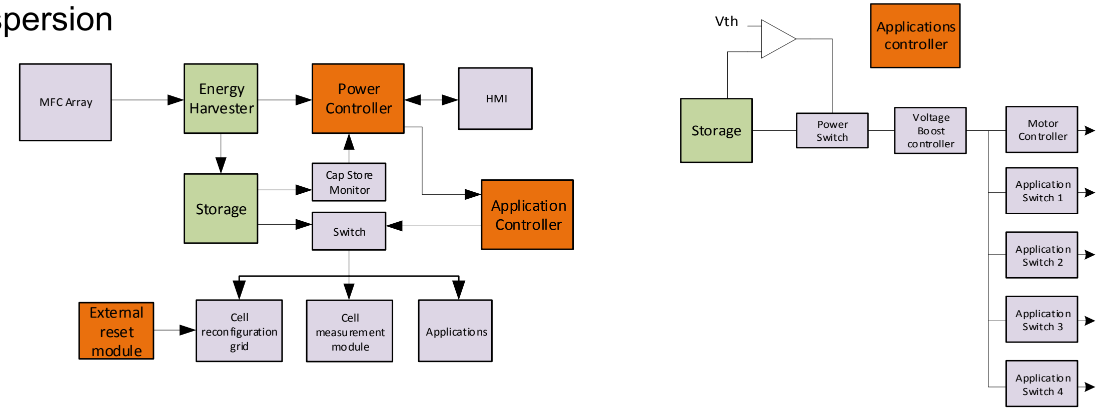
Living Architecture

Wall management
WP 4

Energy Management System

Design objectives

- Harvest maximum energy and simultaneously manage MFC sustainability using data acquisition and cell switching
- As an application demonstration, actuate a window attached to the wall structure using the power generated from the wall
- Demonstrate cold start operation
- Demonstrate the wall as a self-sustaining entity by managing energy collection and dispersion



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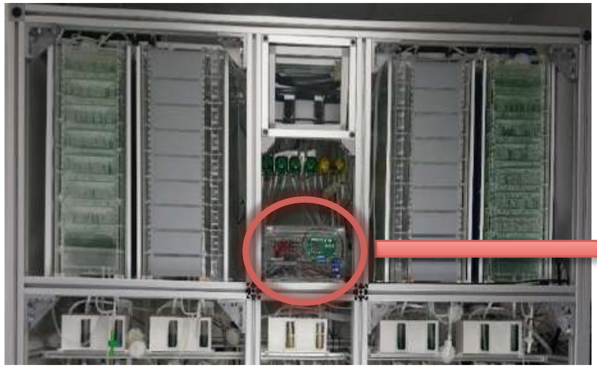
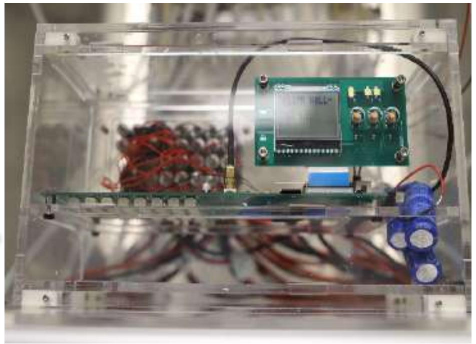
Living Architecture

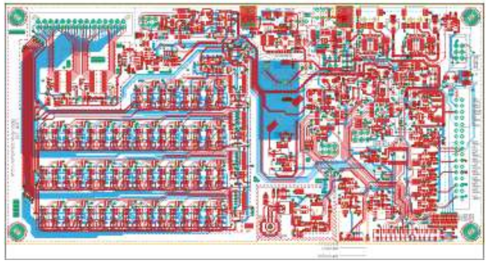
Wall management
WP 4

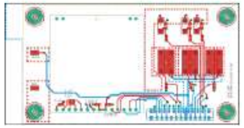
EMS – building and operation





Tasks
- Dynamic reconfiguration
- Data logging
- Window actuation
- Temperature/humidity sensing





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PeePower® urinal – Glastonbury festival

2015

OXFAM

2015

Env. Science: Water Res. & Technol 2 (2), 336-343

2016

Journal of Power Sources 392, 150-158

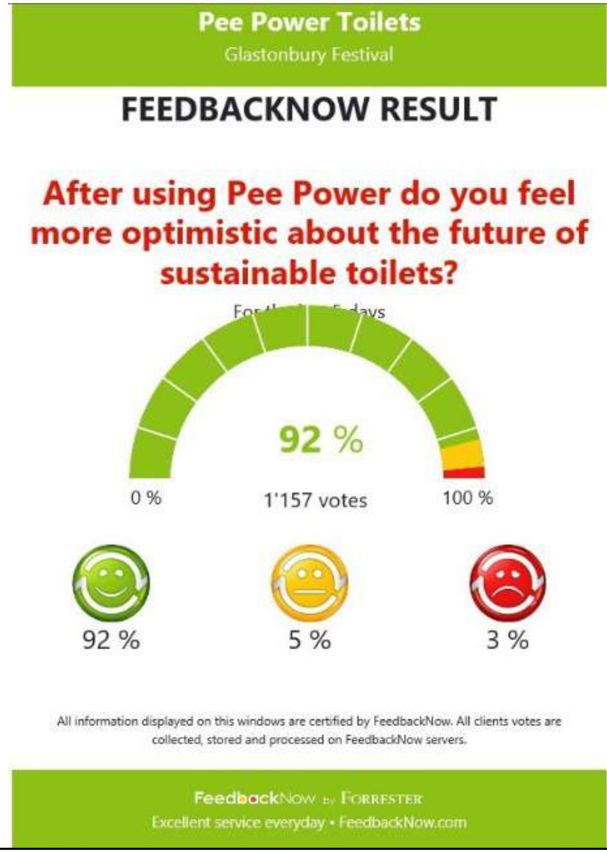
2017

PeePower® urinal – Glastonbury festival

BILL & MELINDA GATES foundation

BBiC Bristol BioEnergy Centre

2019



The PEE POWER® urinal has been field-trialled at the 2015, 2016, 2017 and 2019 Glastonbury music festival, with >1000 people using it per day (≡ 500L·urine/day).

Pee Power® trial in N. Mathare, Kenya

BILL & MELINDA GATES foundation

BBiC Bristol BioEnergy Centre

- 20 MFC modules with 22 MFCs in each box
- 5 boxes in 4 fluidic cascades, connected electrically in parallel
- Integrated pH probe
- Inoculated on 12/06/2018