

1 A BOX–BEHNKEN DESIGN-BASED MODEL FOR PREDICTING POWER
2 PERFORMANCE IN MICROBIAL FUEL CELLS USING WASTEWATER

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7
8 Although modelling is regarded as a useful tool to understand the performance of
9 microbial fuel cells (MFCs), the number of MFC models remains very low compared
10 with the number of experimental works available in the literature. Moreover, there are
11 very few MFC modelling attempts dealing with the use of wastewater as fuel in these
12 devices, which is essential for the practical implementation of MFCs since the potential
13 of this technology lies in the two-fold benefit of wastewater treatment and bioenergy
14 generation. In this work, a four-factor three-level Box–Behnken design was developed to
15 model the electrochemical power generation in two-chamber MFCs using wastewater as
16 fuel. The optimum values of temperature, external resistance, feed concentration and
17 anodic pH that maximized power output were investigated. Optimum conditions were
18 found at $T = 35^{\circ}\text{C}$ and $R = 1\text{k}\Omega$, corresponding to a maximum power density of 0.88
19 $\text{W}\cdot\text{m}^{-3}$, while feed concentration and pH did not show statistical significance in the ranges
20 studied. Thus, a Box–Behnken design-based model as empirical approach could provide
21 an effective tool for the optimization study of MFC systems.

22
23 Keywords: Microbial fuel cells; Modelling; Optimization; Power density; Response
24 surface methodology; Wastewater treatment.

25
26
27 Introduction

28
29 Microbial fuel cells (MFCs) are a promising technology dealing with two of the most
30 pressing issues that modern society has to face such as demands for renewable non-fossil
31 fuels and the needs for usable water (Cheng et al., 2014; Logan et al., 2006; Salar-García
32 et al., 2015). In an MFC, bacteria degrade organic matter present in wastewater producing
33 electrons and protons (Liu et al., 2004; Menicucci et al., 2006). If bacteria are properly
34 attached to a conductive electrode material, electrons released as result of the oxidation

35 reaction at the anode can be transferred to the cathode through an external circuit
36 (Duteanu et al., 2010; Guo et al., 2014; Ortiz-Martínez et al., 2015a). In order to balance
37 the cell, protons go from the anode to the cathode through an internal membrane or
38 separator. Electrons and protons are consumed at the cathode usually in an oxygen
39 reduction reaction (ORR) to form water. Thus, there is an electromotive force in the cell
40 due the half-reactions taking place at the cathode and anode electrodes (Deng et al.,2010;
41 Hernández-Fernández et al., 2015; Yu et al., 2007).

42

43 The levels of power output generated in these devices are still relatively low and therefore
44 research efforts are being concentrated on improving MFC performance (Degrenne et al.,
45 2012; Kiely et al., 2011; Lanas et al., 2014; Wanget al., 2013). Modelling is a powerful
46 tool for studying and optimizing the operation of MFCs because mathematical models
47 can describe the processes that occur in these systems, covering multiple scenarios with
48 significant savings in terms of cost and time. Although there has been a growing interest
49 in MFC modelling in the last years with a resulting increase in the number of MFC models
50 released, this type of work remains scarce in comparison with the number of experimental
51 studies available (Oliveira et al., 2013). Among them, several computational models
52 focusing on the anode as limiting factor have been reported given the importance of
53 biofilm formation in MFCs (Ortiz-Martínez et al., 2015b). The model developed by
54 Marcus et al. (2007) can be highlighted as one of the most prominent models belonging
55 to this group. Their approach focuses on the electrical conduction properties of the biofilm
56 formed in the anode chamber. This one-dimensional model employs the Monod and
57 Nernst equations, anode-based mass balances and Ohm's law to describe the
58 electrochemical performance of the system. Picioreanu et al. (2007) also presented a
59 model based on the microbial activity of the anode, incorporating the Butler–Volmer
60 expression to calculate the current density generated in an electrochemical mediator-
61 based oxidation process. Picioreanu et al. (2008) integrated the before mentioned model
62 with the IWA Model (ADM-1) (Batstone et al., 2002) to cover the competition between
63 anodophilic and methanogenic microbial communities, since methanogenesis
64 phenomenon severely limits MFC efficiency. Pinto et al. (2010) reported a two-
65 population model taking into account the competition between these two types of
66 microbial communities.

67

68 On the other hand, there are a few models studying both the anode and the cathode
69 compartments from an overall viewpoint, avoiding any a priori assumption that the anode
70 is the limiting factor of the system. In this context, Zeng et al. (2010) used the Monod and
71 Bulter–Volmer equations to describe the electrochemical performance of double-chamber
72 MFCs. With a similar approach, Oliveira et al. (2013) followed the model proposed by
73 Zeng et al. (2010) including the study of heat transport phenomena.
74 Sirinutsomboon(2014) presented a comprehensive model for single-chamber MFCs in
75 the absence of separator, comprising the modelling of biofilm formation by the Nernst–
76 Monod equations and distinguishing between endogenous and exogenous respiration
77 processes.

78

79 Finally, there are other works mainly focusing on the modelling of a key process or
80 component, such as ionic transport through ion exchange membranes used as separator in
81 MFCs (Harnisch et al., 2009) or the polarization response of these systems (Wen et al.,
82 2009). Predictive techniques and mathematical algorithms have been also used in this
83 field. Stratford et al. (2014) investigated the capability of several biological indexes in
84 predicting MFC power performance, and Yan and Fan (2013) used fuzzy control
85 combined with PID control to study double-chamber MFCs.

86

87 As can be seen above, several modelling approaches concerning MFCs have been
88 developed. However, the majority of them employ pure substrates and synthetic
89 wastewater prepared in the laboratory (e.g., acetate as carbon source and *Shewanella*
90 *putrefaciens* as bacteria population). There are very few attempts to model MFCs using
91 wastewater, despite the importance of this approach for the practical implementation of
92 MFCs since the great potential of this technology lies in the twin advantage of treating
93 wastewater and generating bioelectricity (Wen et al., 2009). These include the work by
94 Alavijeh et al. (2015a), who proposed a one-dimensional model based on the spatial
95 distributions of the different microorganisms including syntrophic interactions. They also
96 combined several approaches from previous models in order to predict the performance
97 of MFCs using simple and complex substrates such as dairy wastewater (Alavijeh et al.,
98 2015b). Besides, to the best of our knowledge, there is no attempt in the open literature
99 providing Box–Behnken-based empirical models to these devices. This empirical
100 approach offers a useful substitute for pilot scale or scale-up optimization studies.
101 Response surface design methodology (RSM) is based on a sequential set of designed

102 experiments to achieve the optimal response, allowing the relationships between
103 controlled and response variables to be studied for the optimization of a given process.
104 Box–Behnken designs are a well-known optimization tool that has been applied to many
105 chemical processes (Chaichi et al., 2013; Ferreira et al., 2007; Li et al., 2010). This work
106 presents a four-factor three-level Box–Behnken design to describe the electrochemical
107 performance of an experimental two-chamber MFC, studying factors and operational
108 parameters in MFC technology such as temperature, external resistance, feed
109 concentration, and anodic pH that maximize power output.

110

111 Materials and Methods

112

113 Fuel and Reagents

114

115 Wastewater from the primary clarifier of a local wastewater treatment plant was used as
116 organic matter source to inoculate the MFCs set up in the present work (Murcia-Este
117 Plant, Spain). The wastewater used was characterized with a soluble chemical oxygen
118 demand (COD) of 430 mg L⁻¹, total organic carbon (TOC) of 48.5 mg L⁻¹, volatile
119 suspended solids (VSS) of 122% and suspended solids (SS) of 126 mg L⁻¹. The value of
120 soluble COD was fixed at the desired level before each experiment by mixing raw
121 wastewater with high COD wastewater from a local brewery industry (COD = 4100 mg
122 L⁻¹). The final concentration was obtained by solving the set of equations in V₁ and V₂:

123

$$124 \quad V_1 C_1 + V_2 C_2 = V_T C_T \quad (1)$$

$$125 \quad V_1 + V_2 = V_T \quad (2)$$

126

127 where C_T is the desired COD in composite water, V_T is the desired volume in composite
128 water, C₁, and C₂ are the known COD values for wastewater and brewery water,
129 respectively, V₁, and V₂ are wastewater and brewery water volumes, respectively, and V_T
130 is the desired volume in composite water.

131

132 Cathode compartments were filled with phosphate buffer solution, pH 7.0 (monobasic
133 and dibasic potassium phosphates, Sigma-Aldrich, USA). The pH in the anode chamber
134 was adjusted by adding dropwise solutions of acetic acid (for acidic set points) and
135 sodium hydroxide (for basic set points) up to the desired value and monitoring the pH of

136 the mixture by using a pH meter. When COD and pH adjustments were both required,
137 COD adjustment is performed in the first place followed by pH adjustment. These
138 chemicals were purchased at the highest purity available (Sigma-Aldrich, Spain).

139

140 MFC Construction and Operation

141

142 The experimental MFC set-up consisted of double-chambered cells, each comprising two
143 250mL glass bottles to form the anode and the cathode chambers, respectively.
144 Experiments were run in batch mode in cycles of 216 h in the absence of anode
145 recirculation and stirring. The bottles were water-jacketed to keep the operating
146 temperature constant (Schott, Germany). Both chambers were connected with a straight
147 glass tube acting as a bridge (inner diameter of 1.5 cm). A proton exchange membrane
148 Nafion-117 (DuPont Co., USA) acting as separator was placed between the anode and
149 the cathode chambers by using rubber gaskets and 30mm rounded metal joint clips (J.P
150 Selecta, Spain). The temperature of the reactors was controlled with a circulation bath
151 Frigiterm-10 (J.P Selecta, Spain) (minimum cooling temperature of 10°C and a maximum
152 heating temperature of 100°C). An aquarium aerator and porous diffusers were used to
153 supply oxygen to the cathode chamber. Figure 1 shows a schematic representation of the
154 MFC system used for the present work.

155

156 The anode electrodes were made of carbon cloth (E-TEK, USA) while the cathodes
157 consisted of platinized titanium (William Gregor Ltd., UK), both prepared with the same
158 dimensions of 3x2 cm². Nafion-based membranes were pre-treated in oxygen peroxide
159 (30% H₂O₂) and deionized water at 80°C for one hour, respectively, followed by 0.5M
160 H₂SO₄ at 80°C for a further hour. Both electrodes and membranes were kept in deionized
161 water before each use. Electrodes were connected with titanium wires of 30 cm in length
162 (Sigma-Aldrich, USA). In experiments requiring resistance load, anodes and cathodes
163 were connected in closed circuit with an external resistance load of 1 kΩ.

164

165 A central hole was drilled on the anode chamber cap to house the electrode. Oxygen was
166 removed from anode chamber by bubbling nitrogen during the start-up of the MFCs
167 investigated through the anode. Nut-and-septum inserts and polypropylene tubing were
168 used for anode sampling to avoid the exposure of the anode chamber to the open air.

169 Anode chambers were covered with aluminium foil to avoid typical light and temperature
170 day-night cycles.

171

172 Analytical Methods and Measurements

173

174 Organic soluble matter concentration was measured as COD (mg L^{-1}), which is defined
175 as the amount of oxygen necessary to completely oxidize the organic matter contained in
176 a sample. COD measurements were carried out by using the method described in APHA
177 et al. (2005). Anode sampling was conducted on a daily basis. 3 mL of sample were 0.45
178 mm filtered (Millipore, Spain) and then added to a test tube containing enough amounts
179 of COD reagents (Merck, Germany), with a final sample concentration in the 25–1500
180 mg L^{-1} range. Samples were digested during two hours at 150°C in an ECO16
181 thermoreactor (Velp Scientifica, Italy) until reaction was complete. COD was measured
182 in a Spectroquant NOVA 30 (Merck, Germany). The percentage of elimination of soluble
183 organic matter (% COD) is expressed as a percentage with respect to the initial COD. pH
184 measurements were monitored with a pH electrode (Crison Cat. N. 52-04) connected to
185 a pH and conductivity measurement device with temperature compensation (Crison
186 micropH 2000). The accuracy of the measurement was ± 0.01 pH units.

187

188 Voltage was measured by using a DVM-891 digital voltmeter (HQ Power, Germany)
189 clipped to both sides of the external resistance load. Current (I) was calculated from
190 Ohm's law:

191

$$192 \quad I = \frac{E_{cell}}{R_{ext}} \quad (3)$$

193

194 where E_{cell} is the potential of the cell and R_{ext} is the external resistance load.

195

196 Thus, power (P) can be calculated as:

197

$$198 \quad P = \frac{E_{cell}^2}{R_{ext}} \quad (4)$$

199

200 power is usually normalized to one of the characteristics of the MFC reactors. This way,
201 power outputs from different systems can be compared. In this work, power output was
202 normalized to the volume of the reactor. This allows engineering calculations for size and
203 costing of reactors to be performed:

204

$$205 \quad P_v = \frac{E_{cell}^2}{VR_{ext}} \quad (5)$$

206

207 where P_v is the power density (Wm^{-3}) and V is the total reactor volume (empty bed
208 volume).

209

210

211 Results and Discussion

212

213 Box–Behnken Design-Based Model

214

215 The experimental design was selected according to a Box–Behnken matrix (see
216 Supporting Information) with high and low levels determined by the maximum and
217 minimum of the experimental range for each variable, respectively. Temperatures in the
218 experimental space ranged from 15°C to 35°C, wastewater feed concentration from 500
219 to 1500 mg L⁻¹, external resistance from 1 to 100 kΩ and pH from 5 to 9 units. Having
220 these four factors to be investigated, the number of possible scenarios are 28, including 4
221 replicates in order to assess experimental error (experimental numbers 11, 14, 26 and 28
222 in Table I). Experiments were executed in blocks of 8 experiments and in a random order
223 between blocks so that any possible bias from previous results was avoided. The
224 experimental operation of fed-batch MFCs in closed circuit goes through several stages.
225 After an induction phase for the accommodation of microorganisms, there is an
226 exponential growth followed by a stationary phase and a final declining phase. The
227 duration of each phase depends on the initial content of organic matter and the type of
228 oxidant. Examples of the experimental results are depicted in Figures 2 and 3, in which
229 power density and COD removal evolution are plotted as a function of time for some
230 selected experiments. Response used for the model was maximum power density, which
231 typically develops after 24–72 hours depending on the experimental conditions. In this
232 model, the levels of four variables, temperature (T), external resistance (R), wastewater

233 initial concentration (C) and anodic pH was investigated for the maximization of power
 234 density. A summary with all experimental results is shown in Table I, which includes the
 235 maximum power obtained for the conditions established in each scenario. According to
 236 the RSM method, a quadratic model where ε is the experimental error will suit for the
 237 purpose (Equation (4)):

238

$$239 \quad y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{ii} x_i^2 + \sum_{j=2}^k \sum_{i=1}^{j-1} \beta_{ij} x_i x_j + \varepsilon \quad (6)$$

240

241 This empirical model approach is very useful since it is easy to estimate and apply,
 242 especially when little is known about the process. Equation (6) can be rewritten in the
 243 matrix form for our particular case:

244

$$245 \quad [P_V] = [X][\beta] \quad (7)$$

246

247 where matrix $[X]$ represents the independent terms (namely, temperature, external
 248 resistance, wastewater concentration and pH), matrix $[P_V]$ is the volumetric power density
 249 (W m^{-3}), and matrix $[\beta]$ is the matrix of the coefficients of the model. As $[X]$ is not a
 250 square matrix (and consequently it lacks inverse), transposition of matrix X is needed in
 251 order to solve the equation in $[\beta]$:

252

$$253 \quad [\beta] = [[X^T][X]]^{-1}[X][P_V] \quad (8)$$

254

255 Model Resolution

256

257 In this paper, several forms of Equation (6) were solved with the aid of commercial
 258 software Sagata. These forms were linear, linear+interactions, quadratic (without
 259 interactions) and full quadratic (including interactions). An ANOVA analysis was
 260 performed in all cases and regression coefficient (r^2), residual sum of squares (RSS), and
 261 lack-of-fit (p-value) were registered and are summarized in Table II and in detail only for
 262 the full quadratic model in Table III. As can be seen from Table II, the values of r^2
 263 increases and the residual sum of squares (S) reduces as number of parameters in the
 264 model rises. Only quadratic and full quadratic models showed a significant correlation

265 (p-value for lack-of-fit > 0.05). However, even with those models regression coefficients,
266 r^2 values were relatively low (around 90%). The four replicates conducted (experiments
267 numbers 11, 14, 26, and 28) ranged from a power density from 0.029 to 0.179 Wm^{-3} with
268 a mean of 0.102 Wm^{-3} and a standard deviation of 0.057 Wm^{-3} . This limited repeatability
269 is recognized in the literature (Larrosa et al., 2009) and is responsible for the relatively
270 low r^2 and RSS values found with ANOVA.

271

272 A plot of the main effects for the linear model is represented in Figure 4. These plots can
273 be used to compare the magnitudes of the various main effects. A main effect occurs when
274 the mean response changes across the levels of a factor (the red dotted line is the grand
275 mean of the response data). Therefore, the main effect plots can be used to compare the
276 relative strength of the factors. On the other hand, as can be observed in Figure 4, both
277 initial wastewater concentration and pH were not statistically relevant (within the
278 experimental space) for predicting power density as compared to temperature and
279 external resistance. Also although the full quadratic model showed a polished correlation,
280 these parameters showed to be non-significant (p-values > 0.05, 95% confidence).
281 Therefore, in a further refinement they were removed. Finally, the best model for
282 predicting power density was as follows:

283

$$284 \quad P_V \left(\frac{W}{m^3} \right) = 0.09117 + 0.02257 \cdot T - 0.35942 \cdot \log R$$
$$285 \quad \quad \quad + 0.21827(\log R)^2 - 0.01593 \cdot T \cdot \log R \quad (9)$$

286

287 where T represents the cell temperature, log (R) is the common logarithm of the external
288 resistance, C is the wastewater initial concentration, and P is the pH of the contaminated
289 fluid. The ANOVA for this model (see Table IV) shows an acceptable r^2 value balanced
290 with a close to minimal RSS and all its parameters are statistically significant (p-values
291 < 0.05, 95% confidence).

292 A view of the response surface is illustrated as a contour plot in Figure 5(a) and in a three-
293 dimensional space in Figure 5(b). As can be observed, power density increases with
294 temperature while it decreases as logR increases, which would indicate that the response
295 of the system would be favoured by high and low values of temperature and external
296 resistance load, respectively, within the ranges studied. Also, Figure 6 depicts the
297 predicted values vs. observed values. These are scattered randomly along the diagonal

298 not following any pattern, which is in agreement with homoscedasticity hypothesis, in
299 which these designs are based. Normality hypothesis of the data is also guaranteed as can
300 be inferred from the plot of the quartiles of the normal distribution vs. the residuals
301 (Figure 7). Once the prediction equation was shown to be sufficiently strong, it was used
302 to obtain the conditions that maximize power density for the experimental MFCs. In order
303 to make this optimization, partial derivatives of Equation (7) were taken with respect to
304 each one to the factors and were equated to zero:

305

$$306 \quad \frac{\partial P}{\partial T} = 0.02257 - 0.01593 \log R = 0$$

307

$$308 \quad \frac{\partial P}{\partial \log R} = -0.35942 + 0.43654 \log R - 0.01593 T = 0 \quad (10)$$

309

310 The resulting set of two equations was subjected to constrained optimization by using
311 Sagatac. The search was forced into the experimental space in order to avoid finding of
312 unrealistic optimum values. Accordingly, operating conditions that yield maximum
313 power density within the experimental design were found to be $T = 35^{\circ}\text{C}$ and $R = 1 \text{ k}\Omega$.
314 Initial COD concentration and pH do not significantly affect the power within the
315 experimental space studied. Under these conditions, the maximum power density was
316 found to be 0.83 W m^{-3} . The trends marked in this study point out towards optimal
317 performance for the MFC systems studied at high temperatures (i.e., hot climates) and
318 external resistances relatively low within the interval analyzed (microelectronics). On the
319 other hand, COD elimination was higher than 80% in all cases, showing its potential use
320 in wastewater treatment. Finally, initial wastewater concentration within 500–1500 mg/L
321 did not reveal statistical significance on power response and could be considered adequate
322 for the MFC systems investigated. Other works that have studied this parameter in a wider
323 range have reported that feed concentration must be balanced, since high organic load can
324 favour the growth of methanogenic bacteria instead of anodophilic microbial populations.
325 Methanogenic bacteria promote the production of CH_4 in the anode instead of boosting
326 electrical performance, thus affecting the power output obtained (Pinto et al., 2010). In
327 the same way, the effect of pH within the interval 5–9 on power performance was not
328 significant, even when subjected to slightly acid pH conditions ($\text{pH} = 5$). Compared with
329 other modelling approaches commented in the introduction part, Box–Behnken design-
330 based models can present some limitations such as the lack of understanding of the

331 dynamic behaviour of the system. However, it can be especially useful when little is
332 known about the process (Ferreira et al., 2007). Moreover, the optimum values could be
333 used as starting point for searching optimum values with more sophisticated non-linear
334 models.

335

336

337 Conclusions.

338

339 In this work, a four-factor three-level Box–Behnken design was built to predict the
340 electrochemical power generation in two-chamber MFC systems using wastewater as
341 fuel. Optimal values for temperature (T), external resistance (R), wastewater initial
342 concentration (C), and anodic pH were investigated using a quadratic model including
343 linear, linear+interactions, quadratic (without interactions) and full quadratic (including
344 interactions) forms. Operating conditions that yield maximum power density within the
345 experimental design were found to be $T = 35^{\circ}\text{C}$ and $R = 1\text{k}\Omega$, while initial COD
346 concentration and pH did not significantly affect the power within the experimental range
347 tested. More MFC models are expected to be developed in the future due to their great
348 advantages for off-line process optimization, especially models dealing with wastewater
349 for the practical application of MFC technology for simultaneous production of energy
350 and water treatment.

351

352

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354

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Table 1. Summary table with all experimental results

Test	T (°C)	log R	C (mg L ⁻¹)	pH	P _{V,max} (*) (W m ⁻³)	I _{max} (A m ⁻²)
1	25	1	500	9	0.111	3.002·10 ⁻⁵
2	25	1	1500	9	0.172	3.739·10 ⁻⁵
3	35	1	1500	7	0.056	2.141·10 ⁻⁵
4	35	1	1000	9	0.091	2.727·10 ⁻⁵
5	35	2	1000	7	0.015	3.539·10 ⁻⁶
6	25	2	1500	7	0.018	4.752·10 ⁻⁶
7	15	1	500	7	0.056	2.141·10 ⁻⁵
8	15	0	1000	7	0.241	1.406·10 ⁻⁴
9	25	1	500	5	0.327	5.179·10 ⁻⁵
10	35	1	500	7	0.178	3.795·10 ⁻⁵
11	25	1	1000	7	0.029	1.531·10 ⁻⁵
12	15	1	1000	9	0.019	1.239·10 ⁻⁵
13	15	1	1500	7	0.009	8.315·10 ⁻⁶
14	25	1	1000	7	0.070	2.352·10 ⁻⁵
15	15	1	1000	5	0.217	4.221·10 ⁻⁵
16	25	2	500	7	0.024	4.435·10 ⁻⁶
17	15	2	1000	7	0.012	3.094·10 ⁻⁶
11	25	0	1000	9	0.848	2.474·10 ⁻⁴
19	35	0	1000	7	0.881	1.628·10 ⁻⁴
20	25	2	1000	9	0.006	2.294·10 ⁻⁶
21	25	1	1500	5	0.082	2.598·10 ⁻⁵
22	25	0	500	7	0.641	2.293·10 ⁻⁴
23	25	0	1000	5	0.713	2.396·10 ⁻⁴
24	25	0	1500	7	0.508	2.012·10 ⁻⁴
25	25	2	1000	5	0.005	1.912·10 ⁻⁶
26	25	1	1000	7	0.131	3.301·10 ⁻⁵
27	35	1	1000	5	0.130	3.276·10 ⁻⁵
28	25	1	1000	7	0.179	3.817·10 ⁻⁵

(*) Conversion from W m⁻³ to W m⁻² may be accounted by multiplying volumetric power density by a 1.1·10⁻⁴ factor which includes anode specific surface, anodic chamber surface-to-volume ratio and graphite density.

Table 2. Basic statistics of the model studied

Model	$r^2(\%)$	S	Lack-of-fit (p-value)
Linear	61.5	0.1638	0.068
Linear + interactions	66.6	0.1790	0.040
Linear + quadratic	84.2	0.1165	0.0165
Full quadratic	90.1	0.1127	0.0163

Table 3. a) Regression and b) ANOVA data for the full quadratic model

a) Regression

Term	Coef.	SE Coef.	T	P
Constant	0.1022	0.05637	1.814	0.095
T	0.0565	0.03565	1.584	0.139
Log R	-0.3111	0.03565	-8.725	0.000
C	-0.0410	0.03255	-1.260	0.232
pH	-0.0106	0.03255	-0.325	0.751
T*T	-0.0504	0.04827	-1.045	0.317
Log R*Log R	0.2129	0.04827	4.411	0.001
C*C	-0.0009	0.04660	-0.019	0.985
pH*pH	0.0790	0.04660	1.695	0.116
T*logR	-0.1294	0.07130	-1.815	0.095
T*C	-0.0187	0.05637	-0.333	0.745
T*Ph	0.0397	0.05637	0.705	0.494
LogR*C	0.0317	0.05637	0.563	0.584
LogR*pH	-0.0585	0.05637	-1.038	0.320
C*pH	0.0765	0.05637	1.357	0.200
S = 0.1127	$r^2 = 90.1\%$			

b) ANOVA

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	14	138.259	138.259	0.098756	7.77	0.001
Linear	4	0.94458	0.98931	0.247327	19.46	0.000
Square	4	0.34727	0.36040	0.090100	7.09	0.004
Interaction	6	0.09073	0.09073	0.015122	1.19	0.374
Lack-of-fit	9	0.13940	0.13940	0.015489	3.54	0.163
Pure error	3	0.01312	0.01312	0.004374		
Total	26	153.511				

Table 4. a) Regression and b) ANOVA data for the definitive model

a) Regression

Term	Coefficients	SE Coef.	T	P
Constant	0.1161	0.02846	4.079	0.000
T	0.0664	0.03549	1.871	0.045
Log R	-0.3210	0.03549	-9.045	0.000
LogR*LogR	0.2183	0.04549	4.798	0.000
T*LogR	-0.1593	0.06970	-2.285	0.032
S = 0.1138	R ² = 85.4%			

b) ANOVA

Source	Degrees of freedom	Seq SS	Adj SS	Adj MS
Regression	4	125.009	125.009	0.31252
Linear	2	0.92307	106.429	0.53214
Square	1	0.25940	0.29828	0.29828
Interaction	1	0.06763	0.06763	0.06763
Lack-of-fit	3	0.08753	0.08753	0.02918
Pure error	19	0.19479	0.19749	0.01039
Total	26	153.511		

Figure 1. Schematic representation of the MFC system used

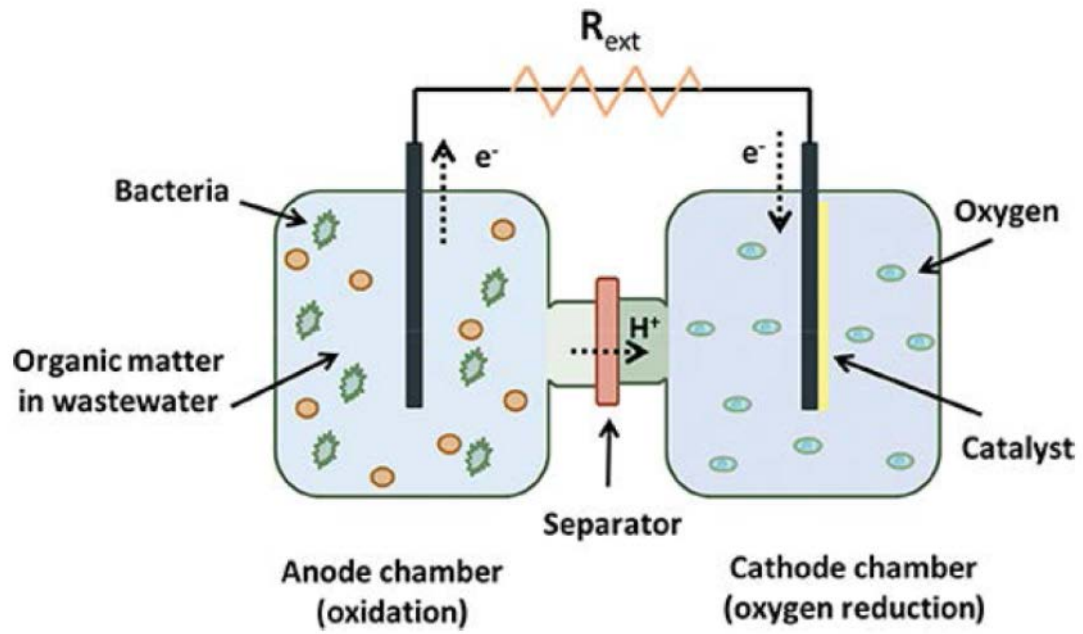


Figure 2. Volumetric power density as a function of time for some selected experiments

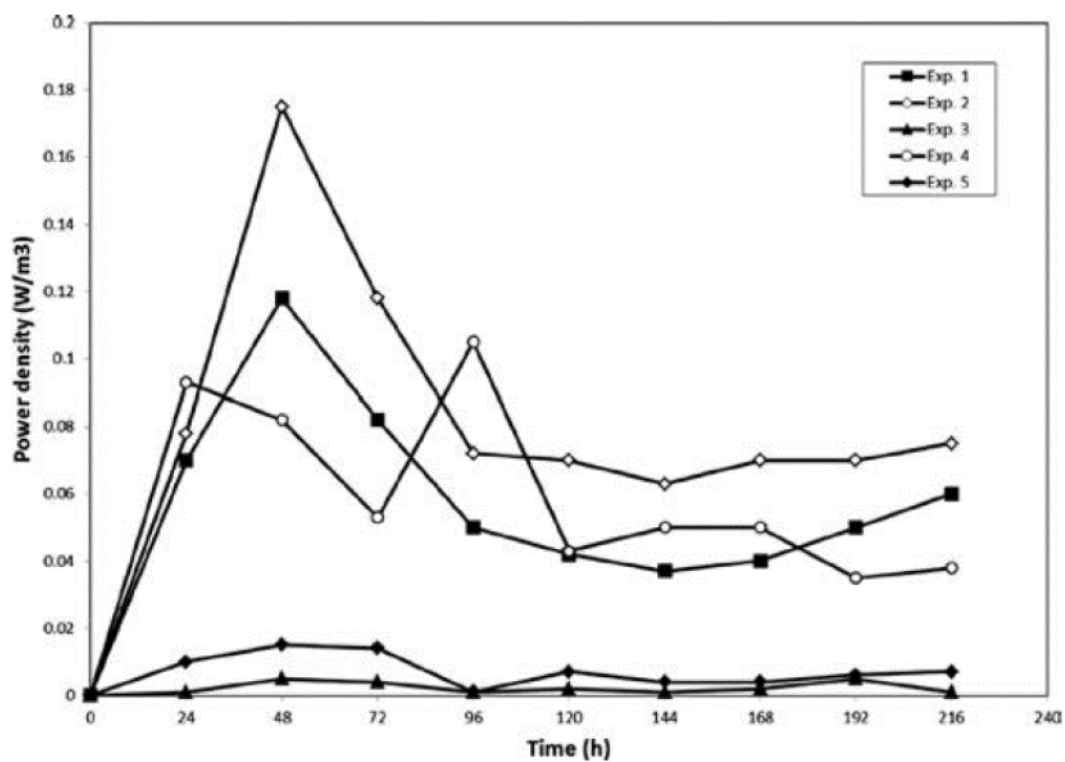


Figure 3. COD evolution as a function of time for some selected experiments.

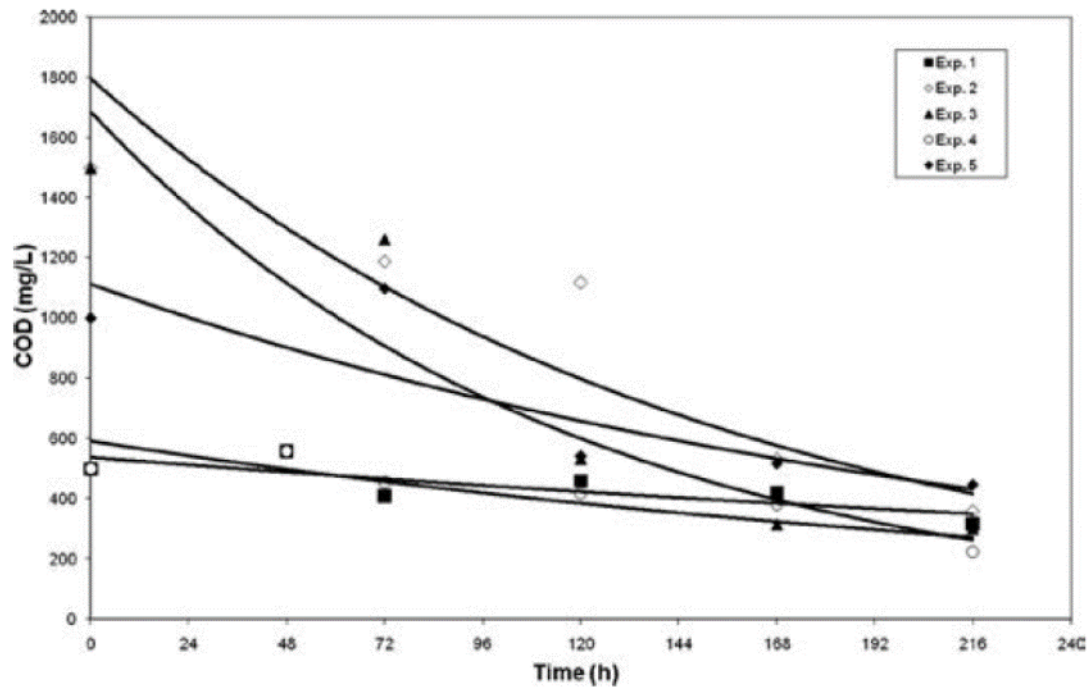


Figure 4. Main effects plots for the linear model.

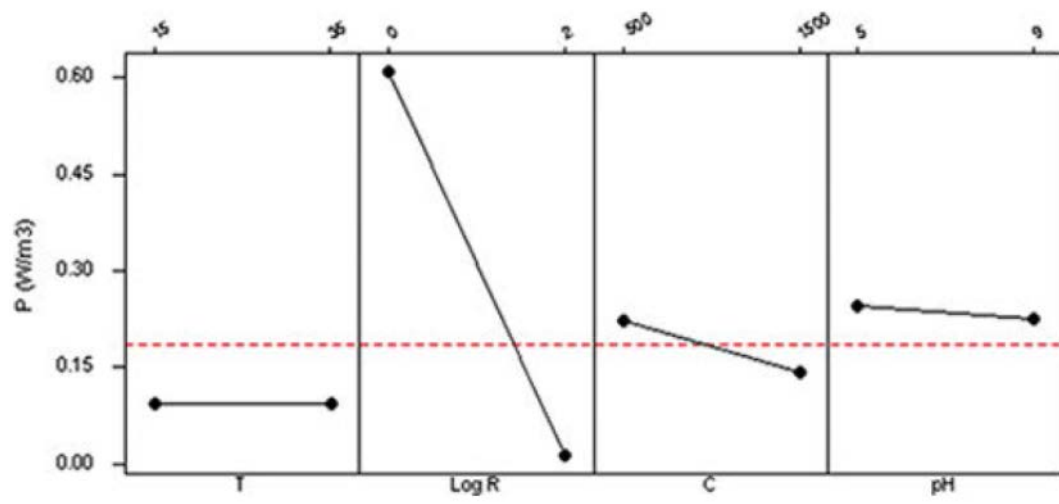


Figure 5. Graphical representation of the response surface as a function of T and R: a) Contour plot; b) Wireframe plot

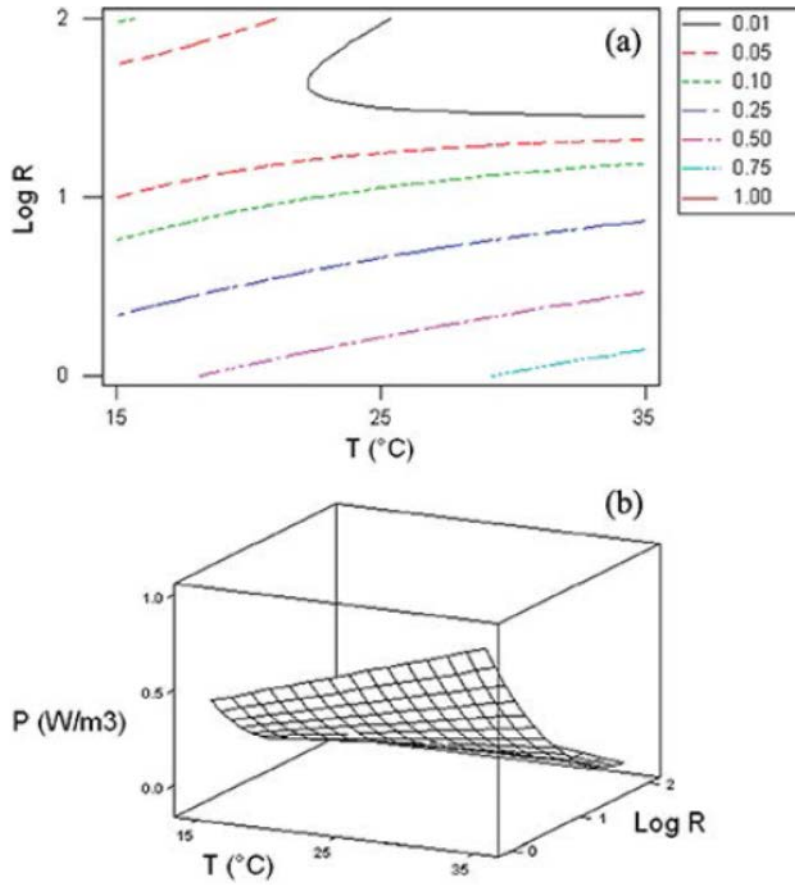


Figure 6. Model prediction vs observed values.

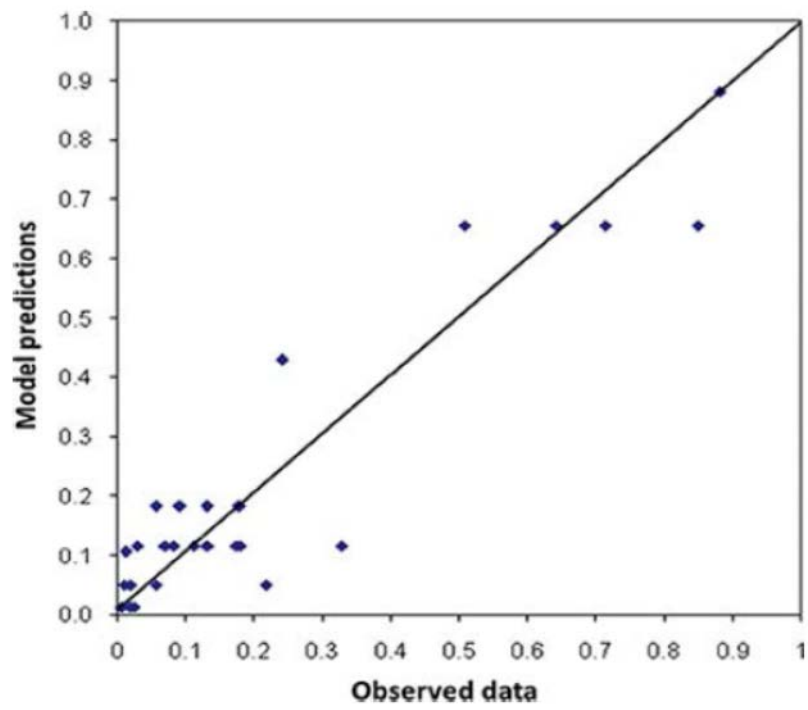


Figure 7. Normality test

