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# 1           **Micro-Combined Heat and Power using Dual Fuel engine and** 2           **biogas from Discontinuous Anaerobic Digestion**

3

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8

## 9           ***Abstract***

10           The modeling of the Micro-CHP unit operating in dual-fuel mode is performed based on  
11           experimental results carried out at the laboratory scale. The engine tests were performed on an  
12           AVL engine, with a maximum power of 3.5 kW, using conventional diesel as pilot fuel and  
13           synthetic biogas as primary fuel. The biogas flow rate is evaluated using the experimental  
14           results from the literature, based on the anaerobic digestion in batch reactor of a mixture of 26  
15           % of Oat Straw and 74 % of Cow Manure, diluted to contain only 4 % of volatile solid.

16           The engine operation was modeled using the Artificial Neuron Network (ANN) method.  
17           Experimental engine tests were used as a database for training and validation phases of ANN  
18           models. Three different ANN models are developed to model respectively the pilot fuel flow  
19           rate, the airflow rate and the exhaust gas temperature. Engine power output, biogas flow rate  
20           and biogas methane content were used as the same input layer.

21           Given that the evolution of the biogas flow evolves along the entire digestion duration (50  
22           days), the simulation work is performed by varying the number of digesters to be used in  
23           parallel mode. It is obtained that the optimal operation condition, minimizing the number of  
24           digesters and using less than 10 % of the energy from diesel fuel, is to use 5 digesters and run

25 the engine under load of 70 %. It is concluded that a micro-CHP unit of 1 kWe, requires a dual  
26 fuel generator with a nominal power of 1 kWe, five digesters and a daily availability of effluents  
27 of 171 kg/day, consisting of 45 kg/day of oat straw and 126 kg/day of cow manure. It can also  
28 produce up to 2.45 kW of thermal power from the exhaust.

### 29 ***Keywords***

30 Micro CHP; Anaerobic digestion; Dual fuel engine; Artificial Neural Network;  
31 Cogeneration.

32

### 33 ***1. Introduction***

34 Combined Heat and Power (CHP) is an important alternative for minimizing primary energy  
35 consumption by optimizing the efficiency of energy conversion units. CHP is also known as  
36 cogeneration, which means the simultaneous generation of electricity and heat from a single  
37 fuel source. The term Micro-CHP is often associated with systems whose electrical power does  
38 not exceed 50 kW [1]. Micro-CHP in farm, where biogas is produced from anaerobic digestion  
39 of effluents, has been of increasing interest to livestock farmers in recent years. Biogas is a  
40 cleaner and potentially renewable fuel. It consists mainly of methane (CH<sub>4</sub>), carbon dioxide  
41 (CO<sub>2</sub>), small traces of carbon monoxide (CO), hydrogen (H<sub>2</sub>), oxygen (O<sub>2</sub>) and hydrogen  
42 sulphide (H<sub>2</sub>S ) [2]. In Europe, biogas represented in 2015 around 8 % of renewable energy  
43 production and the equivalent of 4 % of European natural gas consumption. In 2016, the  
44 treatment of organic waste by anaerobic digestion is largely done on farms. Among the 269  
45 anaerobic digestion units installed in France up to 2016, there are nearly 88.5 % units are on  
46 farms and only 11.5 % in centralized units [3].

47 The most used heat engines in micro-CHP devices are internal combustion engines.  
48 Although the use of gaseous fuel is widespread in spark ignition engines, the high CO<sub>2</sub> content  
49 of the produced biogas by anaerobic digestion, especially at the beginning of the digestion

50 reaction, disadvantages the use of biogas as a fuel in the internal combustion engines. Indeed,  
51 the high CO<sub>2</sub> content in the intake charge has the disadvantage of increasing the specific heat  
52 of the gases and reducing the flame propagation speed [4]. It also decreases the energy quality  
53 of the fuel and thus increases fuel consumption [5].

54 Putting existing diesel engines into dual-fuel operating mode, using diesel as pilot fuel and  
55 biogas as primary fuel, has both environmental and economic advantages [6]. In fact,  
56 Tippayawong et al [7] that reported long-term utility in this second operating mode shows  
57 negligible effects on engine power and efficiency during the first 2000 hours run. Beyond this,  
58 a little quantity of carbon deposition inside the combustion chamber was observed [7]. Different  
59 techniques were examined to improve the operation of compression ignition (CI) engines in  
60 diesel-biogas dual fuel mode such as the use of low levels of substitution [8], preheating of  
61 induced air-fuel mixtures [9,10], modifying the pressure and temperature of the initial charge  
62 using exhaust gas recirculation process [11,12] and modification of the pilot fuel injection  
63 system [13,14].

64 Biogas is often used as the primary fuel in dual-fuel engines because of its high anti-knock  
65 properties compared to other gaseous fuels. With a methane content of up to 65 %, its high  
66 octane number allows it to have greater knock resistance and better adaptation to engines that  
67 generally have higher compression ratios [15]. It was reported that in combined cooling,  
68 heating, and power (CCHP) systems, where production of heat, cold and power occur  
69 simultaneously from the same primary energy, biogas-diesel dual-fuel mode reduces CO<sub>2</sub>  
70 emissions by 24.9 % compared to the single production mode [16].

71 In dual-fuel operating mode and under higher engine loads (above 80 %), the brake specific  
72 energy consumption (BSFC) is slightly lower than that of conventional diesel mode, whereas  
73 the brake thermal efficiency (BTE) in dual-fuel mode is considerably lower than that of diesel

74 mode. On the other hand, under lower engine loads, the lower BTE and the higher BSFC are  
75 generally caused by incomplete combustion of the biogas-air mixture due to a poor mixture and  
76 a lower temperature in the cylinder [17]. Although the BTE is slightly affected under higher  
77 engine loads, it remains largely dependent on CH<sub>4</sub>/CO<sub>2</sub> ratio of the biogas composition [18].  
78 Increasing the CH<sub>4</sub> content of the biogas, which raises the heat release rate, leads to a significant  
79 increase in the BTE [15,19]. However, the substantial replacement of the pilot fuel with the  
80 gaseous fuel causes a remarkable BTE degradation [20]. The gaseous fuel, whose ignition  
81 temperature is much higher than the pilot fuel, will act as heat sink during the combustion  
82 process. It causes an undesirable increase in the specific heat capacity of the working fluid and  
83 consequently, it decreases the combustion temperature [21]. Nathan et al. [22] have shown that  
84 above 40 % of CO<sub>2</sub> in biogas, the dissociation of CO<sub>2</sub> into O<sub>2</sub> and CO significantly affects the  
85 ignition delay.

86 On the other hand, the lower carbon content of CH<sub>4</sub> compared to petroleum-based diesel  
87 reduces the exhaust gases emissions [23]. Several researchers have confirmed that the relative  
88 homogeneous charge and the lower cylinder temperature in dual-fuel operating mode have the  
89 advantage of significant reduction of NO<sub>x</sub> and smoke emissions [21,24,25]. As regards the HC  
90 and CO emissions, they are higher when the biogas substitution is high, especially if its  
91 percentage of CO<sub>2</sub> is high [26]. With regard to the exhaust gas temperature in the dual-fuel  
92 operating mode, it has been shown to be higher than that of the diesel operating mode [27,28].

93 In micro-CHP on farm, the biogas is produced from anaerobic digestion of livestock  
94 effluents whose the characteristics and composition are very random. Anaerobic co-digestion  
95 of livestock effluents and agricultural waste is widely applied in Europe [29,30]. Anaerobic  
96 digestion on the farm, which involves the production of biogas from agricultural biomass, is  
97 becoming increasingly important as it offers significant environmental benefits and provides an  
98 additional source of income for farmers [31]. Livestock effluents in the form of manures

99 (generally semi solid with a high straw content) or slurry (only cattle excrement that is generally  
100 liquid) are of interest for anaerobic digestion because of their high potential of biogas  
101 production.

102 Several studies have been conducted to investigate the increased biogas production through  
103 anaerobic digestion of livestock effluents [32–35]. The potential of biogas production not only  
104 depends on the chemical composition of the effluents, but also on the anaerobic digestion state  
105 (solid state, liquid state, pasty state), type of digesters (continuous reactor, semi continuous  
106 reactor, batch reactor) and on the operating conditions (digestion temperature, recirculation of  
107 percolate ... etc.).

108 In continuous or semi-continuous anaerobic digestion, the composition and flow rate of  
109 biogas leaving the digester are practically constants. Depending on the composition of the  
110 effluents and on the operating conditions, the methane content is often between 55 and 65 %  
111 [36]. The major disadvantage of this pathway is the high investment costs, especially for small  
112 power plants. In France, for example, anaerobic digestion plants with electrical power of 35,  
113 170 and 500 kWe respectively, have the investment costs of 12.5, 5.6 and 5.6 k€/kWe [37]. A  
114 large part of the investment costs is reserved for the biogas storage, its homogenization, sealing  
115 systems and security. This is because the biogas must be produced continuously and with a  
116 methane content between 55 and 65 % to be acceptable in the gas engines. Indeed, a biogas  
117 whose low methane content causes flammability and efficiency problems and a biogas whose  
118 methane content is too high causes the knocking problems in gas engines.

119 In the discontinuous digestion process (batch reactor), where the digesters are sized  
120 according to the size of the farm and the availability of the effluents, the investment and  
121 maintenance costs for the small plants can greatly reduce compared to those of the continuous  
122 digestion process. The most problem is that the flow of biogas leaving the digester and its

123 methane content change throughout the anaerobic digestion time, which is often between 40  
124 and 60 days. The purpose of this study is to overcome these constraints and use this pathway to  
125 develop on-farm micro-CHP technology. It involves two objectives: The first is to use a dual-  
126 fuel engine to use the biogas leaving the digester regardless of its flow and its methane content.  
127 It eliminates the need for biogas storage, which significantly reduces investment costs. The  
128 second objective is to determine the number of digesters needed to optimize the operation of a  
129 micro-CHP unit on the farm. For this purpose, a simulation work of a micro-CHP unit based  
130 on experimental data from laboratory tests was performed. Simulation of the engine  
131 operation in dual fuel mode is carried out using artificial neural network (ANN) models.  
132 The novelty of the present work is to model and develop a diesel engine map, operating in  
133 diesel-biogas dual-fuel mode taking into account the availability of biogas in term of  
134 quantity and quality (composition). This expresses that the operation of the engine is very  
135 flexible to the number of digesters used for the anaerobic digestion of livestock effluents,  
136 which in turn directly influences the primary fuel (biogas) supplied to the engine. In  
137 addition, the model makes it possible to minimize the number of digesters so that the biogas  
138 produced is directed to the engine without storage. As a result, the pilot fuel remains  
139 minimal in accordance with the regulatory limits, making it possible to benefit from the  
140 feed-in tariffs of electricity.

141 ANN is a popular machine learning technique that has been shown its effectiveness in  
142 various fields [38]. This form of black-box modelling approach allows the omission of  
143 physical knowledge or equations that relate the relationship between the input and  
144 corresponding output without the loss of accuracy unlike white and grey box modelling,  
145 albeit care must be taken in the selection of appropriate input and outputs to avoid  
146 meaningless predictions.

147 The engine modeling technique using the ANN models is more preferable nowadays  
148 because it can identify a complicated and unknown input/output relationship based on  
149 experimental data. It has several advantages compared to mathematical engine models  
150 (analytical multi-zone models, computational fluid dynamic models and chemical kinetic  
151 models) which are very difficult to put into practice because excessive assumptions have  
152 been made in constructing the models [39–42]. In addition, these mathematical models  
153 depend on several engine-specific parameters, which are generally difficult to estimate or  
154 to predefine (inlet valve flow coefficient, kinetic of combustion, local air fuel ratio, local  
155 heat loss coefficient...etc.). Furthermore, ANN has a better capability in approximating  
156 input-output relationship that polynomial regression models owing to its ability in capturing  
157 non-linear behavior of a given system in particular for a large number of measured data  
158 [38].

159 Several studies have been conducted on diesel engine performance and/or emissions  
160 modeling using neural network models [39,43–45]. Others have also used this method for  
161 performance modeling and emission characteristics, and even the elaboration of the  
162 operational maps for engines operating with biodiesel blends [46–48]. Similarly for the  
163 modeling of engines operating in dual-fuel mode, researchers are increasingly interested in  
164 the use of the ANN method to model the operation, performance, emissions and even  
165 develop operational maps for the dual fuel engines [49–51].

166 Since the modelling of the diesel engine is a regression task, two situations need to be  
167 considered. The first situation is that the model output is single dimension, which means  
168 that individual model is required for each engine performance output. The other one is with  
169 multi-dimension outputs, where one model is already sufficient to predict several engine  
170 performance outputs. In order to increase the model accuracy and prevent any parameter

171 from dominating the output values, the data sets are often normalized before training the  
 172 models [39,52].

173 This present paper covers three major parts, namely the kinetic production of biogas from  
 174 anaerobic digestion of livestock effluents, the modeling of dual-fuel engine using the ANN  
 175 models, and simulation of the micro-CHP unit operating with dual fuel engine and using  
 176 biogas as primary fuel. The dual fuel engine setup, the pilot fuel characteristics, the ANN  
 177 models as well as the kinetics production of biogas are briefly introduced in Section 2. The  
 178 ANN based models were trained and validated using a series of experimental tests,  
 179 performed with a 3.5 kW dual fuel engine. The engine models outputs are single dimension.  
 180 The first is to model the pilot fuel flow rate, the second is to model the airflow rate and the  
 181 third is to model the temperature of the exhaust gas. The instantaneous production of biogas  
 182 is determined from the literature where anaerobic digestion of a mixture of oat straw and  
 183 cow manure was studied and optimized [53]. In section 3, where the main results are  
 184 discussed, the engine tests, the validation of the ANN models, as well as the simulation  
 185 results of the micro-CHP unit, were presented.

186 ***Nomenclature***

AC	annual consumption	$\dot{H}$	thermal power (W)
AMFR	average mass flow rates	IA	injection angle (degree)
ANN	artificial neuron network	IVC	inlet valve close (degree)
BDC	bottom dead center	IVO	inlet valve open (degree)
BSFC	brake specific energy consumption	LHV	lower heating value (J/kg)
BTE	brake thermal efficiency	$\dot{m}$	mass flow rates (kg/s)
CA	crank angle	MR	mass ratio
CCHP	combined cooling, heating, and power	MSE	mean square error
CHP	combined heat and power	OS	oat straw
CM	cow manure	$R^2$	regression coefficients
CI	compression ignition	RMSE	root mean square error
$C_p$	specific heat (J/kg.K)	RNG	rundum number generation
ER	energy ratio	TDC	top dead center

EVC	exhaust valve close (degree)	TS	total solid
EVO	exhaust valve open (degree)	VS	volatile solid

187

## 188 *2. Materials and methods*

### 189 *2.1. Dual-fuel engine setup*

190 The engine tests were carried out on a single cylinder research engine (AVL 5402),  
 191 instrumented to control and measure the operating parameters. The main design specifications  
 192 as well as the technical operating data are given in Table 1.

193

*Table 1 : Dual-fuel engine specification*

<b>Parameter</b>	<b>Specification</b>
Model	AVL 5402
Type	Four-stroke, CI engine
Bore x Stroke	85 x 90 mm
Compression ratio	17.3
Injection pressure	600 bar
Combustion system	Dual-fuel
Injection system type	Common rail, direct injection
Nozzle hole x diameter	5 x 0.17 mm
Rated power output	3.5 kW at 1500 rpm
IA	7° CA before TDC
IVO	36° CA before TDC
IVC	69° CA before BDC
EVO	76° CA before BDC
EVC	32° CA before TDC

194

195 Under the same operating conditions, including air-fuel ratio, engine speed and engine loads,  
 196 the performance parameters of this engine, despite being an water-cooled single-cylinder diesel  
 197 engine, can be projected on a multi-cylinder engine that can be used in a CHP unit. During the  
 198 tests, the engine speed was kept constant at 1500 rpm, similar on to that of electric power  
 199 generator, producing electricity at a frequency of 50 Hz. All tests were carried out to develop

200 an engine power ranging between 1.75 and 3.5 kW. The pilot fuel is a conventional diesel,  
201 while the primary fuel is a synthetic biogas, consisting of CH<sub>4</sub> and CO<sub>2</sub>.

202 The experimental procedures consists in fixing the biogas methane content and the pilot fuel  
203 flow rate and maintaining the desired engine load acting on the biogas flow rate. It consists in  
204 varying the CH<sub>4</sub> content of biogas between 20 and 60 % and the engine load between 50 and  
205 100 % (i.e. engine power outlet between 1.75 and 3.5 kW). The recorded data from each test  
206 are the engine power, biogas methane content, biogas flow rate, pilot fuel flow rate, airflow  
207 rate, and exhaust gas temperature.

## 208 ***2.2. Fuels characteristics***

209 The flow rate of the synthetic biogas as well as its CH<sub>4</sub> content have been varied to obtain a  
210 wide range and to get closer values to the biogas composition resulting directly from the  
211 digesters, without using a storage gasometer. The latter is often necessary to balance the flow  
212 rate and composition of biogas (50 to 65 % CH<sub>4</sub>) for subsequent use.

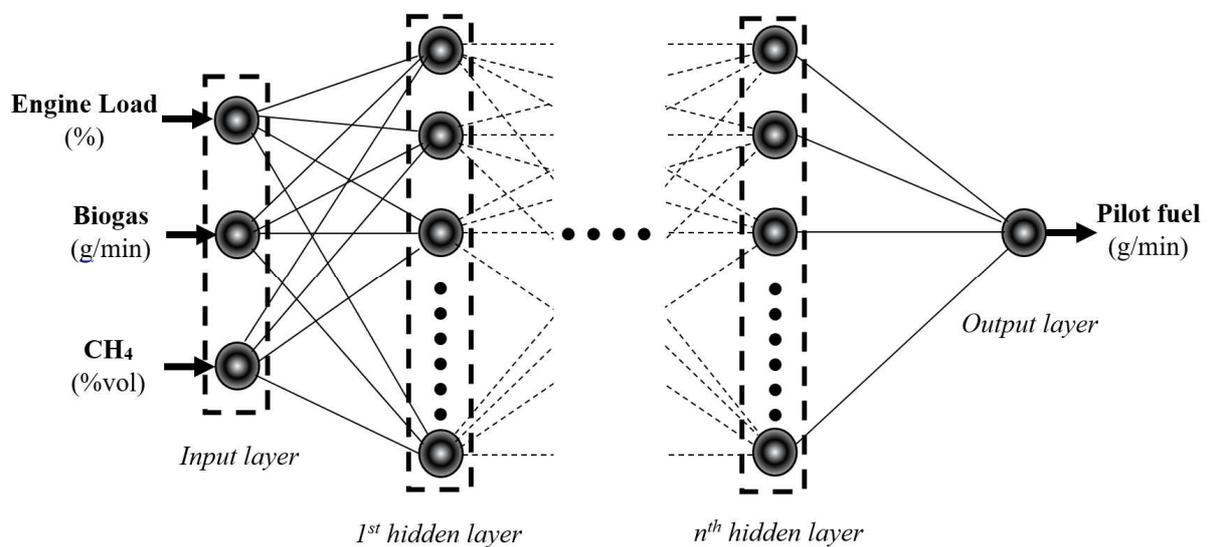
213 In practice, the biogas characteristics from anaerobic digestion of cattle effluents, such as  
214 flow rate and CH<sub>4</sub> content, vary throughout the entire digestion period, which is of the order of  
215 two months. In this study, the biogas is synthetized from pressurized bottles. The methane  
216 content of the synthesis gas varies from 20 to 60 % while its flow rate is adjusted to develop  
217 the desired engine load (between 50 to 100 % of full load).

218 The pilot fuel, which serves as an ignition source for the mixture, is a conventional fuel  
219 consisting of 93 % v/v diesel (C<sub>20</sub>H<sub>40</sub>) and 7 % v/v biofuel (C<sub>18</sub>H<sub>36</sub>O<sub>2</sub>). Its density and lower  
220 heating value (LHV) are 840 kg/m<sup>3</sup> and 42.8 MJ/kg, respectively.

## 221 ***2.3. Engine parameters modeling***

222 The engine parameters have been modeled using methodology based on Artificial Neural  
 223 Networks. An ANN is an architecture containing a huge quantity of neurons systematized in  
 224 different layers and the neurons of one layer are linked to those of another layer of by dint of  
 225 weights, and it can be prepared or trained to accomplish a specific duty via creating accurate  
 226 alteration of its linking weights, bias and architecture [43,44].

227 In this study, ANN based models have been developed in the MATLAB environment using  
 228 the Neural Network toolbox. The proposed ANN model consist in three discrete ANNs,  
 229 developed to estimate engine parameters namely pilot fuel flow rate, intake airflow rate and the  
 230 exhaust gas temperature. Where, ANN1 is used to delineate pilot fuel flow rate, ANN2 is used  
 231 to delineate intake airflow rate, and ANN3 is used to delineate exhaust gas temperature. Each  
 232 ANN has one input layer with three variables (engine power, biogas flow rate and its CH<sub>4</sub>  
 233 content), up to five hidden layer and one output. Figure 1 illustrates the architecture of the  
 234 ANN1 model for the pilot fuel flow rate.



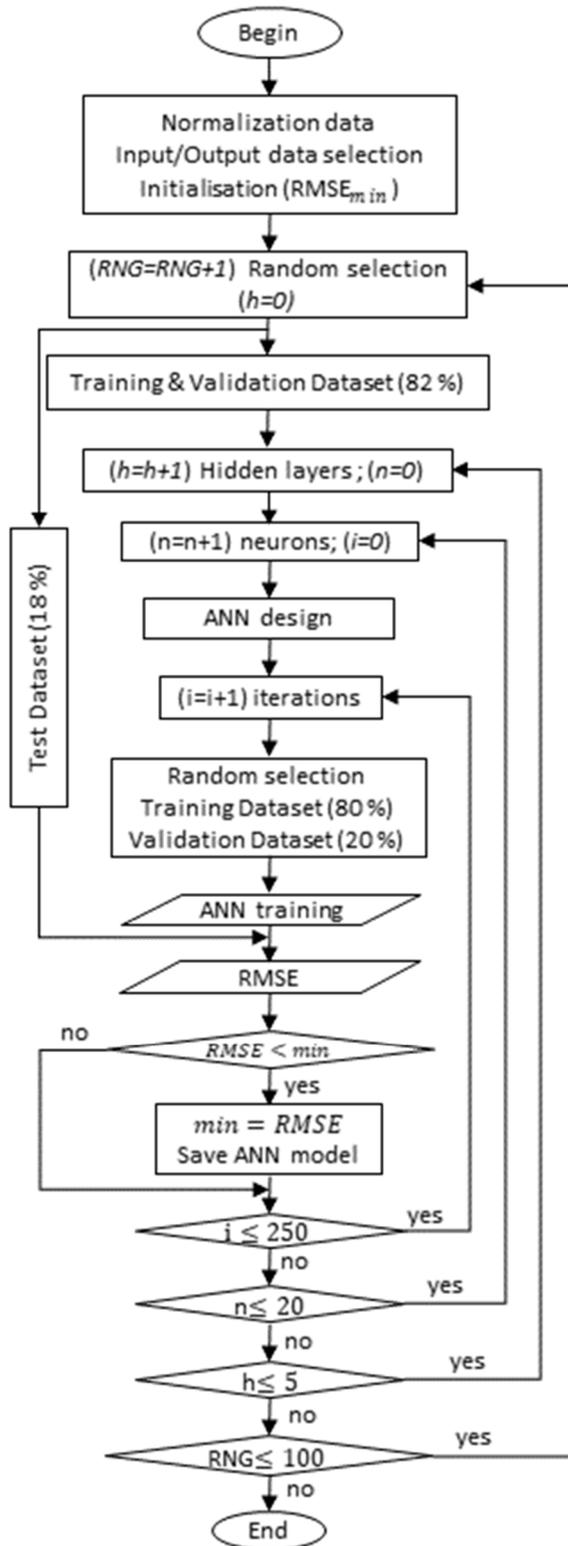
235  
 236 *Figure 1. Configuration of multi hidden layers neural network estimating pilot fuel flow*  
 237 *rate*

238 The implementation of ANN comprises of three main stages viz. parameter selection,  
239 training, and testing. As regard the parameter selection, the input-output data is often processed  
240 by normalizing it within a certain range [38,43]. The recorded data from the experimental tests  
241 (83 tests) is then normalized and randomly partitioned with respect to training, testing and/or  
242 validation. They are divided into two sets of which the first (68 tests) is selected as the training  
243 (80 %) and validation (20 %) dataset, while the second (15 tests) is selected to testing the  
244 generalization capability of ANN models. The training dataset is used to train the model and  
245 tuning model hyperparameters (weights and biases). The model sees and learns from this data.  
246 The validation dataset is used to evaluate a given model, but this is for frequent evaluation. It  
247 is used to fine-tune the model hyperparameters. The test dataset provides the gold standard used  
248 to evaluate the model. It is only used once a model is completely trained (using the train and  
249 validation sets). Since the choice of the test dataset significantly influences the model training,  
250 the control random number generation (RNG) function of Matlab software is used to control  
251 the random selections of the results and an optimal selection has been made for each model. It  
252 consists in choosing the selection that minimizes the RMSE among the 100 different random  
253 selections. Normalized parameters such as engine power, biogas flow rate, methane content,  
254 pilot fuel flow rate, airflow rate and exhaust gas temperature respectively were obtained by  
255 dividing their values by 4 kW, 60 g/min, 100 % v/v, 20 g/min, 300 g/min and 600 °C.

256 After selecting the input and output parameters, the key parameters specified prior to any  
257 ANN investigation are the number of hidden layers, the number of neurons in the hidden layers,  
258 the activation function, as well as the training (learning) algorithms. Since there is no precise  
259 rule to determine the number of hidden layers and the number of neurons in the hidden layer,  
260 the trial and error method has been applied to find the number of hidden layers and the number  
261 of neurons in the hidden layer. In order to decide the most appropriate or best solution a software  
262 was developed to design and train the network by varying the number of hidden layers from 1

263 to 5 and the number of neurons in each hidden layer from 1 to 20 neurons. Figure 2 illustrates  
264 the calculation flowchart for selection data optimization, ANN model design optimization, and  
265 ANN model training.

266



267

268

Figure 2. Flowchart of the design and optimization of the ANN models

269

For each design, 250 iterations were performed where the new obtained optimal design is

270

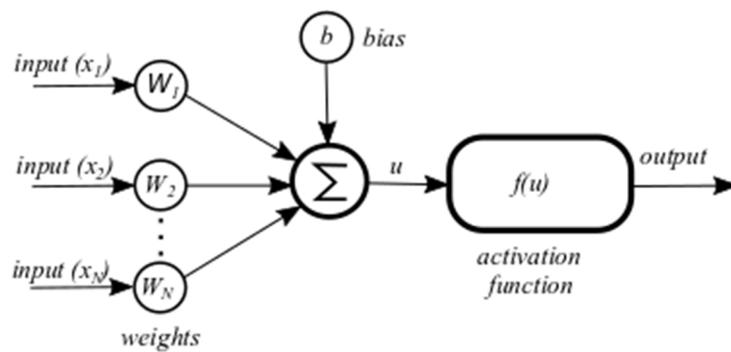
updated. The optimum solution has been selected by minimizing the root mean square error

271 (RMSE), given by Eq.1. Indeed, various studies have been shown that the application of ANN  
 272 method in engine performance consists of optimal configurations consisting of using one to two  
 273 hidden layers whose number of neurons in each layer does not exceed ten [43–45,54].

274 
$$RMSE = \sqrt{\frac{\sum_{i=1}^n (Output\_Cal_i - Output\_Mes_i)^2}{n}} \dots\dots\dots (Eq.1)$$

275 Where :  $Output\_Cal_i$  and  $Output\_Mes_i$  are respectively the  $i^{th}$  calculated and measured  
 276 output values. ( $n$ ) is the total number of the measured output data.

277 As shown in figure 1, the fully connected layer method is considered, i.e. each neuron is  
 278 connected to every neuron in the previous layer, and each connection has it's own weight. Each  
 279 neuron of hidden layer is molded by input(s), addition block and activation function followed  
 280 by the output. The weight is a value that defines the strength of the input connected to the node.  
 281 A bias controls the magnitude of the input for the activation function, in which the magnitude  
 282 is increased with a positive bias and vice-versa. The computational model is given by the  
 283 perceptron model in figure 3 [54].



284

285 Figure 3. The perceptron model

286 The general expression of the output of the model is

287 
$$u = b + \sum_{i=1}^N w_i x_i \dots\dots\dots (Eq.2)$$

288 The output of the perceptron model is governed by the activation (transfer) function. The  
289 hidden layers are governed by the log-sigmoid activation function (logsig) while the output  
290 layer is governed by the linear activation function (purelin). The log-sigmoid activation  
291 function (Eq.3) takes the input (which can be any value between plus and minus infinity) and  
292 overwrites the output in the range 0 to 1. The linear activation function (Eq.4) leaves the input  
293 as it is.

294  $f(u) = \frac{1}{1+e^{-u}}$  ..... (Eq.3)

295  $f(u) = u$  ..... (Eq.4)

296 The gradient descent with momentum backpropagation training function (traingdm) is used  
297 as learning algorithms. It consists in adjusting the network parameters, namely the weights and  
298 the biases, by using as a cost function the mean squared error (MSE). The network parameters  
299 are backpropagated until the signal is minimized upon a number of training iterations, which is  
300 also known as epochs.

301 **2.4. Simulation of biogas production**

302 The evolution of biogas production (flow rate and CH<sub>4</sub> content) from cattle manure effluents  
303 were simulated based on previous research works [53]. In fact, the cattle manure effluents,  
304 especially in small farms, are often mixed with straw. Zhao et al [53] investigated the anaerobic  
305 co-digestion of oat straw (OS) and cow manure (CM). Their study examined the effects of  
306 different percentages of total solid (TS) and the addition of CM on methane production during  
307 OS anaerobic digestion. The experiments were conducted at a laboratory scale on 300 ml loads  
308 in 500 ml laboratory flasks. The batch tests were carried out in an enclosure maintained at a  
309 constant temperature, at 37 ± 2 °C, for a maximum of 50 days. This time, usually chosen as  
310 hydraulic retention time T<sub>95</sub>, is considered optimal for the anaerobic digestion reaction. It  
311 makes it possible to produce 95 % of methane which can be produced when the reaction time

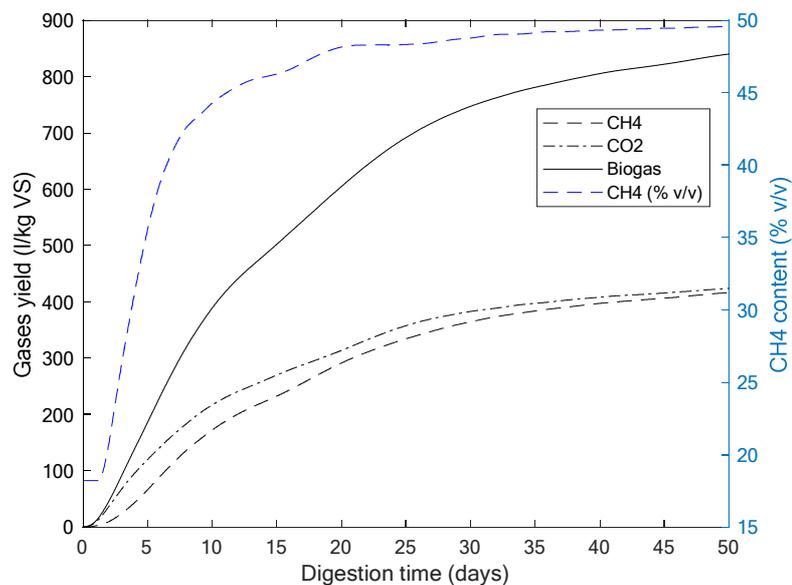
312 is maintained until the completion of the reaction. Table 2 summarizes the OS and CM  
 313 characteristics.

314 *Table 2 : Characteristics of OS and CM*

Parameter	OS	CM
Total solid (%)	94.73 ± 0.42	16.8 ± 0.19
Volatile solid (%)	86.61 ± 0.66	9.22 ± 0.08
Cellulose (%)	29.87 ± 1.14	22.91 ± 0.28
Hemicellulose (%)	30.12 ± 1.35	22.85 ± 0.11
Lignin (%)	5.23 ± 0.22	8.09 ± 0.08
Ash (%)	14.36 ± 0.26	6.32 ± 0.17
Total carbon (%)	36.35 ± 0.31	26.27 ± 0.14
Total nitrogen (%)	0.67 ± 0.01	1.20 ± 0.04
Carbon/Nitrogen ratio	54.25	21.89

315

316 The produced biogas characteristics, in particular the cumulative production of the main  
 317 chemical species (CH<sub>4</sub> and CO<sub>2</sub>) constituting biogas, divided by the input charge in volatile  
 318 solids (VS), are represented in Figure 4. The highest cumulative production of biogas was  
 319 obtained with a mixture of OS:CM ratio of 2:1 and a TS content of 4 %. It was 840 L<sub>biogas</sub>/kg<sub>VS</sub>  
 320 consisting of 49.6 % of CH<sub>4</sub> and 50.4 % of CO<sub>2</sub>.

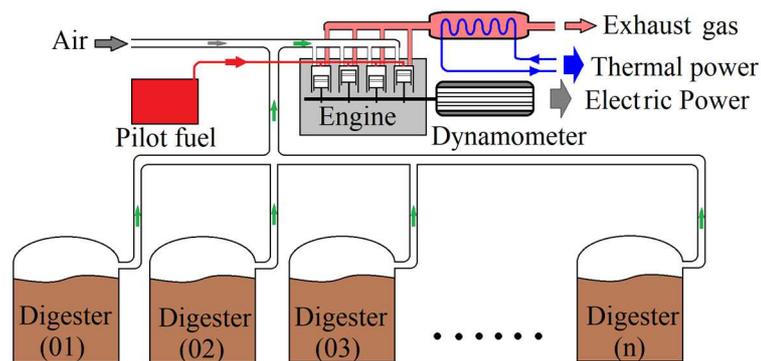


321

322 *Figure 4. Cumulative production of biogas from Co-digestion of OS and CM at 37 °C*

323 The cumulative production curves summarize the evolution of the total production of biogas  
324 per kg of VS of feedstock. This feedstock represents a mixture of 0.889 kg of OS and 2.495 kg  
325 of CM, diluted with 29.41 kg of water to contain only 4 % of TS. After 50 days of anaerobic  
326 digestion, the cumulative production is 840 liters of biogas, consisting of 416 liters of CH<sub>4</sub> and  
327 424 liters of CO<sub>2</sub>.

328 The shape of the cumulative biogas production curve will be used in simulation work as a  
329 flow of biogas from each digester. It allows to model the dual-fuel operating mode without  
330 biogas storing gasometer, where the biogas from the anaerobic digesters is directed directly to  
331 the intake of the dual-fuel engine (Figure 5).

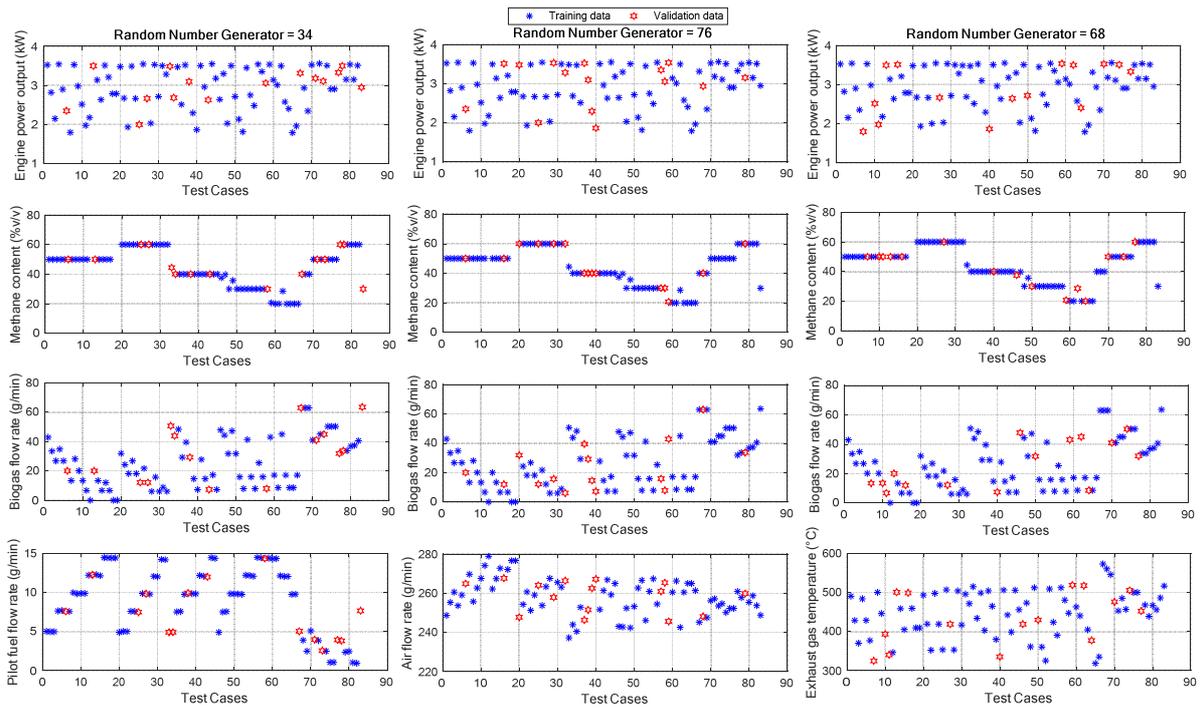


332  
333 *Figure 5. Schematic of the CHP plant operating with biogas from n digesters*

### 334 **3. Results and discussion**

#### 335 **3.1. Engine tests**

336 The experimental results used to train, validate and test the ANN models are presented in  
337 Figure 6. It summarize the selected input data (engine power, biogas methane content, biogas  
338 flow rate) and the selected output data of the ANN models (pilot fuel flow rate, airflow rate,  
339 and exhaust gas temperature).



340

341

*Figure 6. Experimental tests and the optimal random selection of the training and validation data*

342

343

The training and validation dataset is presented in blue color while the test dataset is presented in red color. It is clear that the optimal selection of the test dataset differs for each model. The optimum choices of the test dataset for models ANN1, ANN2 and ANN3 respectively are obtained using the control random number generation (RNG) of 34, 76 and 68. It is obvious that the choices of the test dataset are different. This is because the physical models that connect the model outputs to their inputs (engine power, biogas methane content and biogas flow rate) are also different.

350

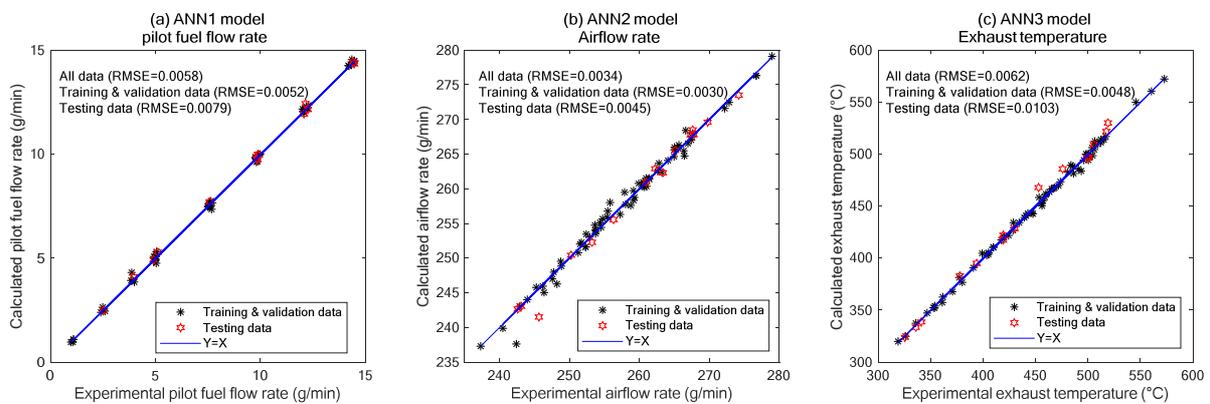
The results allow us to draw two conclusions: The first is that the chosen experimental procedure makes it possible to scan all the possible cases and to have a very representative experimental set. The second is that the control random selection of the test dataset plays a key role in the ANN modeling. Indeed, uncontrolled random selection risks selecting unrepresentative or undiversified dataset.

354

355 **3.2. Performances and validation of ANN based models**

356 The models are validated using two criteria namely RMSE and R-squared ( $R^2$ ). The RMSE  
357 is an absolute measure of fit, whereas R-squared is a relative measure of fit. RMSE is a good  
358 measure of how accurately the model predicts the response, and it is the most important criterion  
359 for fit if the main purpose of the model is prediction. It indicate how close the observed data  
360 points are to the model's predicted values. Lower values of RMSE indicate better fit. With  
361 regard the R-squared, it has the useful property that its scale is intuitive: it ranges from zero to  
362 one, with zero indicating that the proposed model does not improve prediction over the mean  
363 model, and one indicating perfect prediction.

364 It is found that the optimal configurations of the models ANN1, ANN2 and ANN3  
365 respectively have the RMSE values of 0.58 %, 0.34 % and 0.62 % and the regression  
366 coefficients ( $R^2$ ) values of 0.9993, 0.9858 and 0.9959. The propinquity of the  $R^2$  values to (1)  
367 and RMSE values to (0) signifies the accurateness of the ANN based models [43,55]. It reflect  
368 that these ANN models give quite satisfactory and acceptable performance. This suggests that  
369 the ANN model of the engine is accurate, valid and reliable. The performance graphs for the  
370 networks with good agreement between experimental and calculated results are shown in Figure  
371 7.



372

373 *Figure 7. Experimental versus calculated values for the different recorded parameters*

374 The good precision and steadfastness of the ANN based models also reflect the good choice  
375 of the inputs parameter selection of the models, such as engine power, biogas methane content  
376 and biogas flow rate. Indeed the fact that the engine power depends on the fuels flow rates (pilot  
377 and primary fuels) adequately justifies the physical dependence of the ANN1 model output  
378 (pilot flow rate) with the engine power, biogas flow rate and biogas methane content. Regarding  
379 the physical dependence of the airflow rate (ANN2 model output), it is related to the model  
380 inputs through the admitted flow of biogas. Indeed, the intake flow of the engine, naturally  
381 aspirated under a constant engine speed (1500 rpm), consists of the sum of two flows, namely  
382 the airflow and the biogas flow (biogas flow rate and its methane content). As for the physical  
383 dependence of the airflow rate to the engine speed, it is already explained in the physical  
384 dependence of the parameters of the ANN1 based model, where the biogas flow rate and the  
385 engine speed are physically dependent. For the physical dependence of the ANN3 model  
386 parameters, it is evident that the exhaust gas temperature depends on the engine power, biogas  
387 flow rate, and biogas methane content (i.e. CH<sub>4</sub> and CO<sub>2</sub> flow rates). In the diesel engine, where  
388 under a constant engine speed the volumetric efficiency is practically constant, the variation of  
389 the power implies the variation of the air fuel ratio which is in turn affects the exhaust  
390 temperature. In addition, the variation of the biogas flow and the methane content implies the  
391 variation of the CO<sub>2</sub> flow rate, which is an inert gas and therefore its presence decreases the  
392 exhaust temperature.

393 As regards the ANN1 based model, its optimal configuration consists of two hidden layers  
394 for which the first comprises five neurons and the second comprises four neurons. Their optimal  
395 adjusted network parameters, namely the weights and the biases, are shown in Table 3.

396 *Table 3. Weight and biases of the ANN 1 based model*

1 <sup>st</sup> Hidden layer : $IW_{j,i}$					$b_{1,j}$
1.5733	-3.2675	-2.6178	-12.4954		4.6390

0.6322	-1.7464	-2.7040	0.1185		-2.5938
-0.0659	-0.2166	-0.3591	0.1678		1.3898
17.0472	63.1983	3.9064	23.0693		33.2631
0.3928	-0.1054	4.9590	-1.5147		-5.7573
2 <sup>nd</sup> hidden layer : $IW_{j,i}$					$b_{2,j}$
-0.1093	-33.2032	-18.4208	-0.0635	-2.2667	12.5516
30.9308	-30.9775	5.0478	-24.3578	-2.6255	-9.9047
110.3573	16.8241	11.4910	-10.4912	-23.9237	11.3550
0.0259	-0.6688	13.4434	0.0250	0.9057	-8.2412
Output hidden layer : $LW_{j,i}$					$b_3$
-19.1421	0.0824	11.6260	-27.5964		14.6475

397

398 Where,  $i$  = input variables,  $j$  = Hidden layer neurons ,  $IW_{j,i}$  = weight to  $j^{\text{th}}$  neuron of hidden  
399 layer from  $i^{\text{th}}$  input variable,  $LW_{j,i}$  = Weight to output layer from  $j^{\text{th}}$  neuron,  $b_{1,j}$  = bias to  $j^{\text{th}}$   
400 neuron of 1<sup>st</sup> hidden layer,  $b_{2,j}$  = bias to  $j^{\text{th}}$  neuron of 2<sup>nd</sup> hidden layer,  $b_3$  = bias to  $j^{\text{th}}$  neuron of  
401 output layer.

402 For the ANN2 based model, its optimal configuration also consists of two hidden layers for  
403 which the first comprises three neurons and the second comprises five neurons. Their optimal  
404 adjusted network parameters, namely the weights and the biases, are shown in Table 4.

405

*Table 4. Weight and biases of the ANN 2 based model*

1 <sup>st</sup> Hidden layer : $IW_{j,i}$					$b_{1,j}$
-0,0045	-2,4101	6,3145	0,0066		-5,4061
0,0022	0,6448	-0,3752	0,0110		-0,3895
-17,4060	62,4664	-20,2027	95,2348		-24,6803
2 <sup>nd</sup> Hidden layer : $IW_{j,i}$					$b_{2,j}$
-53,2753	-3,8107	-1,1256			52,4951
88,1274	175,1971	46,5783			-119,3185
-11,8383	2,2070	-0,1461			6,1280
12,0424	36,1368	-0,5266			-17,2298
-82,8240	-170,4725	-36,7020			113,9552
Output hidden layer : $LW_{j,i}$					$b_3$
45,7544	41,9136	-9,3538	-78,7266	46,7049	-14,6489

406

407 Likewise, for the ANN3 based model, its optimal configuration consists of two hidden layers  
 408 for which the first comprises five neurons and the second comprises three neurons. Their  
 409 optimal adjusted network parameters are shown in Table 5.

410 *Table 5. Weight and biases of the ANN 3 based model*

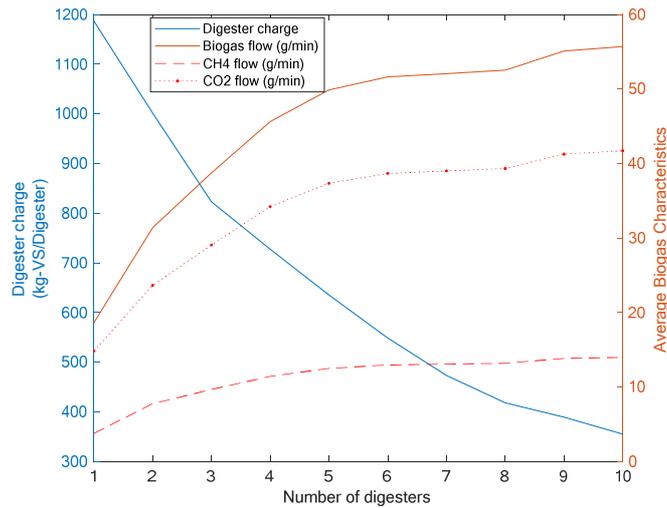
1 <sup>st</sup> Hidden layer : $IW_{j,i}$					$b_{1,j}$
0,1504	0,0775	-1,2412	-1,3139		0,5200
0,5634	-1,0624	4,5390	-2,5093		-1,4359
-0,0130	-0,0178	0,2789	0,2887		-1,6385
1,4895	-30,0325	2,9975	-7,4717		-1,0186
0,4957	-18,3654	15,7180	-17,7499		3,0818
2 <sup>nd</sup> Hidden layer : $IW_{j,i}$					$b_{2,j}$
-0,7228	-0,1800	12,8054	-0,5347	-0,6179	-1,4763
6,9956	2,4618	9,0203	0,6300	1,3695	-9,2359
5,4879	4,2692	-11,4440	0,5861	1,9571	-7,3014
Output hidden layer : $LW_{j,i}$					$b_3$
16,6370	37,2658	-25,8575			-12,9805

411

### 412 **3.3. CHP simulation results**

413 It is recalled that the engine used, with a maximum power of 3.5 kW, has been able to  
 414 consume up to 60 g/min of biogas (Figure 6). Given that the digesters dump the biogas into a  
 415 manifold (as shown in Figure 5), the anaerobic digestion unit will be sized so that the maximum  
 416 flow rate of biogas in the manifold outlet is 60 g/min.

417 The instantaneous flow rate of biogas leaving a single digester is determined by deriving the  
 418 cumulative instantaneous production of the digester, given in Figure 4. Depending on the  
 419 number of digesters to be used, the resulted average biogas flow rate and the corresponding  
 420 digester charge are determined. Figure 8 shows the evolution of the digester charge as well as  
 421 the average biogas characteristics (biogas, CH<sub>4</sub> and CO<sub>2</sub> flow rates) as a function of the number  
 422 of used digesters.



423

424

*Figure 8. Digester charge and characteristics of the produced biogas versus number of*

425

*digester to produce a biogas flow rate whose maximum is 60 g/min*

426

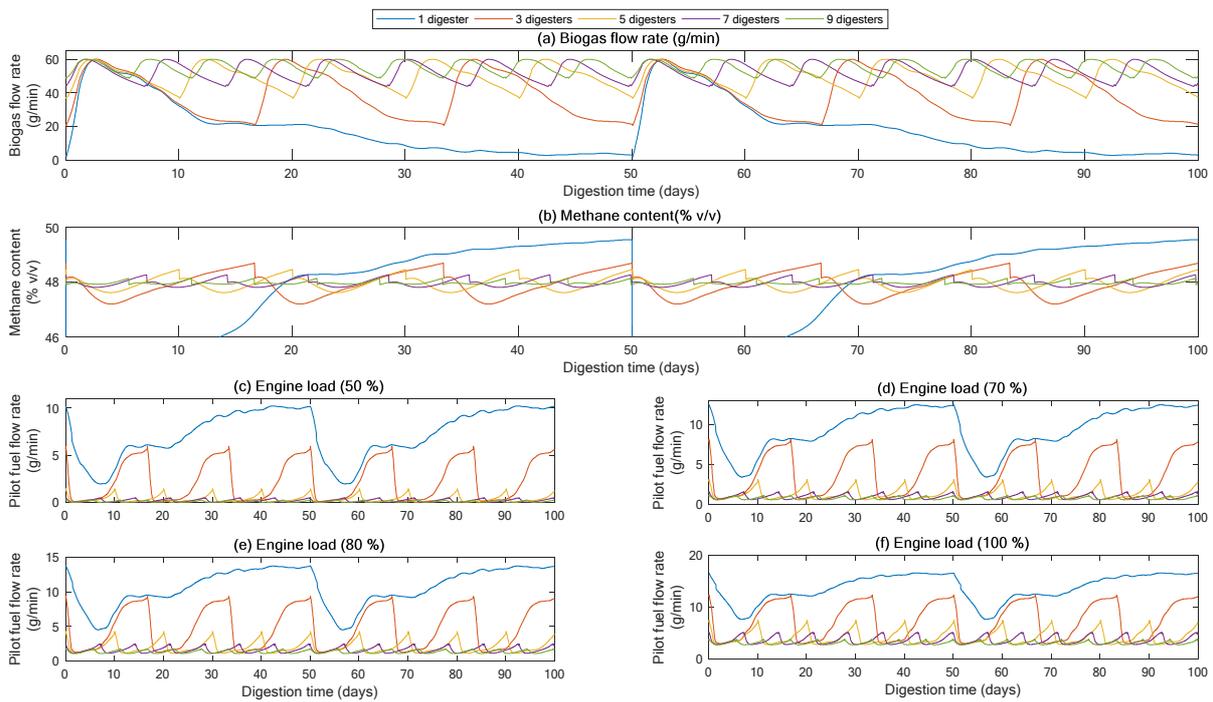
It is observed that when only one digester is used, the amount of effluent (digester charge) is 1187 kg<sub>vs</sub> (mixture of 1055.2 kg of OS, 2961.6 kg of CM and 34909 kg of water). This charge gradually decreases to reach 355.1 kg<sub>vs</sub> (mixture of 315.7 kg of OS, 885.97 kg of CM and 10444 kg of water), for each digester, when 10 digesters are used.

430

It can be noted that the average biogas flow rate increases as the number of digesters increases. This is because the fluctuation of the biogas flow rate decreases while increasing the number of digesters. Indeed, when using two digesters, for example, the loading of the digesters takes place every 25 days. i.e. while the second digester has reached its 25th day of digestion, the first digester has reached its end of digestion (50<sup>th</sup> day) so it will charge again. On the other hand, when using ten digesters, for example, the digesters are loaded every 5 days. i.e. while the tenth digester has reached its 5<sup>th</sup> day of digestion, the first digester has reached its end of digestion (50<sup>th</sup> day). This reduction in the loading time actually has two advantages: the first is to reduce the fluctuation of the flow and the composition of the biogas, the second reduces the storage time of the effluents, which prevents the loss of the methane production yield of the effluents.

440

441 Figure 9.a shows the instantaneous production of biogas flow over a period of 100 days. In  
 442 the case of a single digester, the fluctuation of the biogas flow rate is between 2 and 60 g/min.  
 443 Fluctuations are reduced and range between 38 and 60 g/min when the number of digesters  
 444 exceeds 5. The biogas flow rate becomes less fluctuating. In addition, the biogas methane  
 445 content (Figure 9.b), which varies between 18 and 50 % when a single digester is considered,  
 446 quickly becomes stable, between 46 and 49 %, as soon as two digesters have been considered.



447  
 448 *Figure 9. Biogas flow rate and the corresponding pilot fuel flow rate for different engine*  
 449 *power outputs.*

450 This biogas, whose flow rate and CH<sub>4</sub> content vary over time, serves as the primary fuel for  
 451 the operation of the 3.5 kW power engine in dual fuel mode. This involves the variation of the  
 452 associated pilot fuel flow rate that will be injected into the engine cylinder to develop the desired  
 453 engine load. Figures 9-c to 9-f show the effect of the number of digesters as well as the evolution  
 454 of the pilot fuel flow rate associated with biogas flow rate as a function of the engine load (50,  
 455 70, 80 and 100 %).

456 Using these simulation results (Figure 8 and Figure 9), the performance of the dual fuel CHP  
 457 plant will be evaluated on an annual basis (8760 hours). Figure 10 illustrates the average annual  
 458 pilot fuel flow rate as well as the pilot fuel mass ratio as a function of the engine load and the  
 459 number of digesters. The pilot fuel mass ratio is given by the following equation:

460 
$$MR_{pilot\ fuel} = \frac{AMFR_{pilot\ fuel}}{AMFR_{pilot\ fuel} + AMFR_{biogas}} \dots\dots\dots (Eq.5)$$

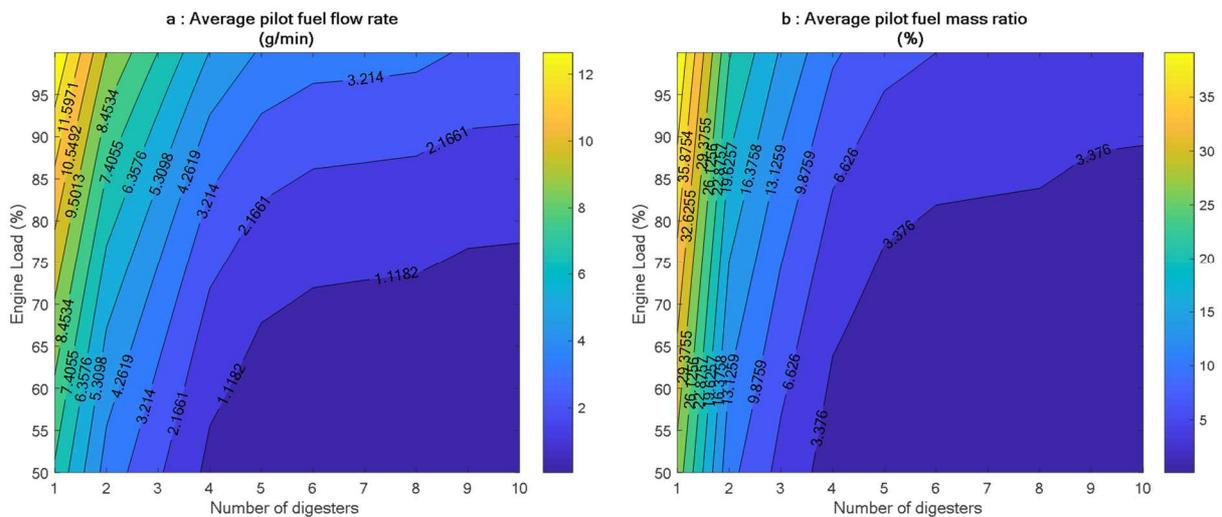
461 Where  $AMFR_{pilot\ fuel}$  and  $AMFR_{biogas}$  are the average mass flow rates for pilot fuel and  
 462 biogas respectively. They are determined as the ratio of annual consumption of the considered  
 463 fuel to the elapsed time of digestion. They are given by the following equations:

464 
$$AMFR_{pilot\ fuel} = \frac{AC_{pilot\ fuel}}{annual\ digestion\ time} \dots\dots\dots (Eq.6)$$

465 
$$AMFR_{biogas} = \frac{AC_{biogas}}{annual\ digestion\ time} \dots\dots\dots (Eq.7)$$

466 Where  $AC_{pilot\ fuel}$  and  $AC_{biogas}$  are the annual consumptions of pilot fuel and biogas  
 467 respectively, calculated by integrating their flow rate curves throughout the digestion time.

468



469

470 *Figure 10. Average annual fuel consumption versus engine load and number of digesters. a)*  
 471 *Average pilot fuel mass flow rate. b) Average pilot fuel mass ratio.*

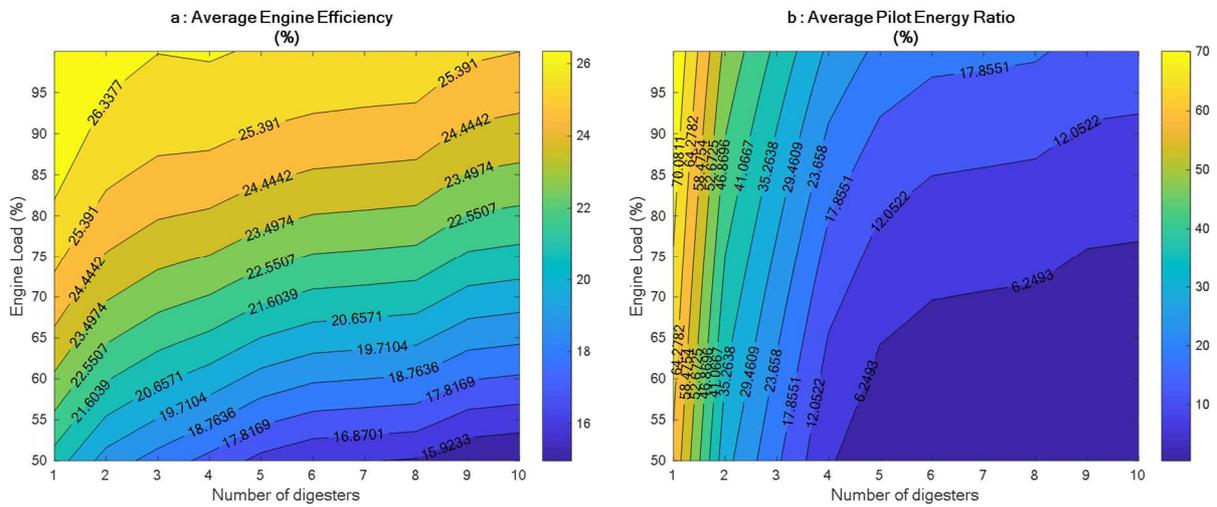
472 The result shows that for a lower number of digesters, the average pilot fuel flow rate  
 473 increases quickly with respect to the engine load. In the case of a single digester, for example,  
 474 the pilot fuel flow rate increases from about 7 to 13 g/min when the engine load increases from  
 475 about 50 to 100 %. This is because the biogas flow rate and its methane content show a  
 476 significant fluctuation. The effect of the number of digesters becomes unimportant from 6  
 477 digesters, where the pilot fuel flow rate goes from about 1 to 3.7 g/min when the engine load  
 478 goes from 50 to 100 %. With regard to the mass fraction of the pilot fuel (figure 10.b), and  
 479 under a given engine load, it decreases by increasing the number of digesters so that it becomes  
 480 negligible when the number of digesters becomes greater than four digesters. This is the  
 481 consequence of the flow rate and methane content of biogas becoming stable.

482 One of the limiting factors for the development of micro-CHP technology with dual fuel is  
 483 the use of diesel fuel as a pilot fuel. The regulated tariffs for electricity from renewable sources  
 484 generally requires limited consumption of fossil fuels for the operation of the CHP plants. For  
 485 instance, in France, the current regulation imposes that the annual fossil energy consumption  
 486 rate should not exceed 10 % of the primary energy used in the diesel-biogas CHP plants [56].  
 487 Figure 11 shows the average energy ratio of the pilot fuel ( $ER_{pilot\ fuel}$ ) as well as the engine  
 488 efficiency as a function of the engine load and the number of digesters. These two parameters  
 489 are given by the following equations:

490 
$$ER_{pilot\ fuel} = 100 * \frac{AMFR_{pilot\ fuel}LHV_{pilot\ fuel}}{AMFR_{pilot\ fuel}LHV_{pilot\ fuel}+AMFR_{biogas}LHV_{biogas}} \dots\dots\dots (Eq.8)$$

491 
$$Engine\ efficiency = 100 \frac{Engine\ power\ output}{AMFR_{pilot\ fuel}LHV_{pilot\ fuel}+AMFR_{biogas}LHV_{biogas}} \dots\dots\dots (Eq.9)$$

492 Where  $LHV_{pilot\ fuel} = 42.42\ MJ/kg$  is the lower heating value of pilot fuel and  $LHV_{biogas}$   
 493 is the lower heating value of biogas. The latter is calculated according to the methane content  
 494 of biogas.



495  
 496 *Figure 11. Engine efficiency and energy ratio versus engine load and number of digesters*

497 Regarding the engine efficiency, it increases proportionally with the engine loads. In  
 498 addition, for a constant engine load, the increase in the number of digesters implies a slight  
 499 decrease in engine efficiency. For a load of 70 %, for example, the engine efficiency goes from  
 500 about 25 % when a single digester is considered to about 20 % when the number of digesters is  
 501 10. This is because increasing the number of digesters induces an increase in the biogas flow  
 502 rate (Figure 8), which causes a decrease in the pilot fuel flow rate (Figure 10-a) at a constant  
 503 engine load. In fact, several researchers reported that increasing the amount of biogas in a dual  
 504 fuel engine at the expense of pilot fuel involves the reduction of engine efficiency [4,8,57–59].  
 505 On the other hand, the pilot fuel energy ratio, shown in Figure 11-b, decreases while increasing  
 506 the number of digesters. It is only from 4 digesters that the average pilot energy ratio is less  
 507 than 10 % which complies with French regulation. For operation under an engine load equal to  
 508 70 %, the number of five digesters can be optimal. In addition to these regulation limits, such  
 509 as thermal efficiency, pollutant emissions, engine aging and maintenance costs, the technical

510 limits has also proven that operation under partial loads is recommended. Aklouche et all [42]  
511 have already proved that the indicated thermal efficiency obtained in dual fuel operation is  
512 almost similar for partial loads greater than 70 %. Finally, this partial load, which represents 70  
513 % of the maximum engine power, actually represents a nominal power of 2.45 kW.

514 For instance, in the case of five digesters, the digester charging period, given as the digestion  
515 time (50 days) divided by the number of digesters (5 digesters), is 10 days. Each digester charge  
516 is then equal to 635.6 kg<sub>vs</sub> (Figure 8) leading to a total inlet charge of 20844 kg (565 kg of  
517 OS, 1586 kg of CM and 18693 kg of water). It provides an average biogas flow rate of 50 g/min,  
518 consisting of 48 % v/v of average methane content (Figure 8).

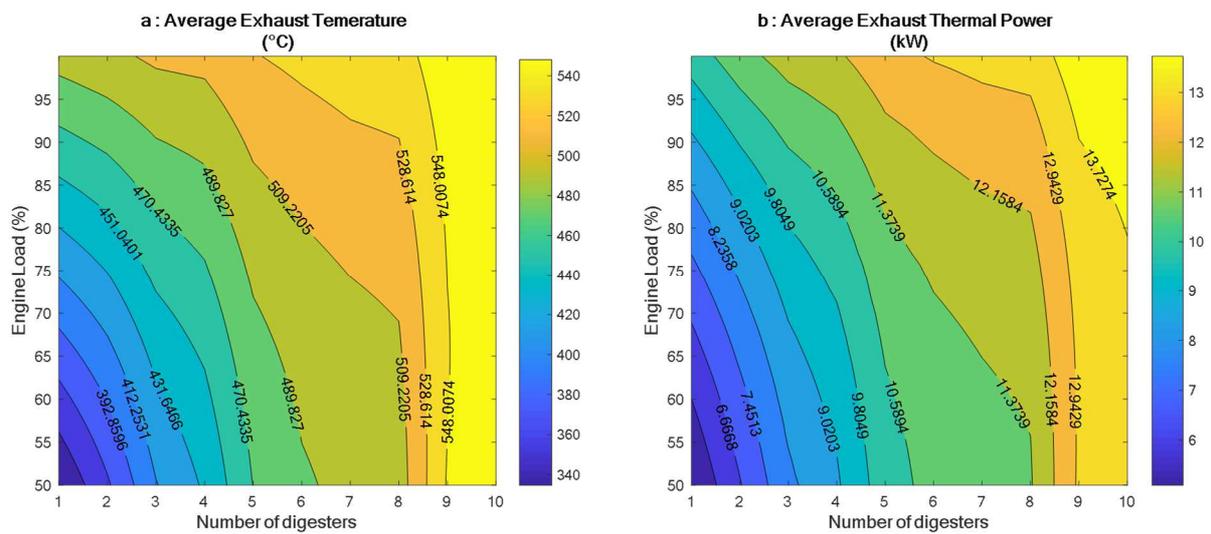
519 In summary, a micro-CHP unit of 1 kw (shaft power) require a dual fuel engine generator  
520 whose nominal shaft power is 1 kW, five digesters and a daily availability of effluents of 171  
521 kg/day, consisting of 45 kg/day of OS and 126 kg/day on CM.

522 Since the thermal power of the CHP plant depends on the heat exchanger efficiencies as well  
523 as the temperature of the cold source, the study is limited to the estimation of the power heat  
524 output available in the exhaust gases. In order to estimate the thermal power, it is necessary to  
525 determine the mass flow rate of the exhaust gases, their temperature and their specific heat. As  
526 regard to the mass flow rate of the exhaust gases, it is given as the sum of input mass flow rates,  
527 such as biogas flow rate, pilot fuel flow rate and airflow rate admitted into the cylinder. The  
528 latter is determined using the ANN2 based model. It allows determining the required airflow  
529 rate according to the engine load and the number of digesters.

530 Using ANN3 based model, simulation results show that the annual average airflow rate range  
531 from 232 to 260 g/min. This is due to the dependence of the airflow rate with respect to the  
532 biogas flow rate, admitted into the engine through its intake manifold. In addition, the fact that  
533 the engine speed is constant does not imply that the airflow rate must be constant. Indeed, the

534 airflow admitted into the cylinder depends on the flow of the biogas injected into the intake  
 535 duct, and which takes part in the total intake flow sucked by the engine. Various studies have  
 536 already found this dependence of intake flows, which sometimes results in the variation of the  
 537 total air fuel ratio [60,61].

538 Regarding the exhaust temperature, it is determined using the ANN3 based model. Figure  
 539 12-a illustrates the average annual exhaust gas temperature as a function of engine load and  
 540 number of digesters. It is in the range of 340 and 540 °C. Unlike water-cooled engines, where  
 541 some of the exhaust energy is absorbed in the engine cylinder head, the temperature of the  
 542 exhaust is often higher. It varies according to the engine load and the air fuel ration [61]. Its  
 543 increase with the number of digesters is due to the fact that the latter favors the use of biogas at  
 544 the expense of the pilot fuel. The relatively high presence of biogas flow rate leads to a decrease  
 545 in the airflow rate, which in turn favors the raising of the exhaust temperature. In fact, the high  
 546 presence of air (or the lower air-fuel ratios) implies the reduction of the quantity of air in excess,  
 547 which absorbs a quantity of heat released by the combustion of the fuels.



548  
 549 *Figure 12. Exhaust gas temperature and the thermal power output versus engine load and*  
 550 *number of digester*

551 A reciprocating internal combustion engine CHP system can provide total efficiency  
552 (electrical power and thermal energy) of up to 80 % [64]. The heat generated from the engine  
553 can be used for numerous purposes such as space heating, cooling, domestic hotwater and other  
554 processes of energy recovery from waste such as pyrolysis, gasification, trans-esterification,  
555 anaerobic digestion, ...etc.

556 To properly estimate the thermal power of exhaust gases, it is necessary to determine their  
557 specific heat according to their chemical composition. Under the assumption of actual complete  
558 combustion, the exhaust gas consists mainly of H<sub>2</sub>O, CO<sub>2</sub>, N<sub>2</sub> and O<sub>2</sub>. The presence of O<sub>2</sub> on  
559 the one hand and the non-presence of the unburned species (CO, HTC, and NO<sub>x</sub>) on the other  
560 hand imply that the real combustion is considered. The estimation of the CO<sub>2</sub> and H<sub>2</sub>O flow  
561 rates are determined using the complete combustion of the pilot and primary fuels while the  
562 estimation of N<sub>2</sub> and O<sub>2</sub> flow rates are determined taking into account the airflow rate sucked  
563 by the engine. Finally, this assumption makes it possible to neglect the presence of the unburned  
564 species, which are evaluated in ppm range in the exhaust gases [22,62], and consequently, their  
565 presence does not affect the specific heat of the exhaust gases. Therefore, the mass fraction of  
566 each species in the exhaust gases is calculated as a function of the biogas flow rate, its methane  
567 content, the pilot fuel flow rate and the airflow rate.

568 The specific heat of each chemical species is given by a correlation as a function of  
569 temperature [63]. The specific heat of the exhaust gases ( $Cp_{Exhaust\_Gas}$ ) is then determined  
570 using Equation 10.

$$571 \quad Cp_{Exhaust\_Gas}(T) = x_{H_2O}Cp_{H_2O}(T) + x_{CO_2}Cp_{CO_2}(T) + x_{N_2}Cp_{N_2}(T) + x_{O_2}Cp_{O_2}(T) \text{ .. (Eq.10)}$$

572 Where  $Cp_{H_2O}(T)$ ,  $Cp_{CO_2}(T)$ ,  $Cp_{N_2}(T)$ ,  $Cp_{O_2}(T)$  are the specific heats in [J/kg.K] of H<sub>2</sub>O,  
573 CO<sub>2</sub>, N<sub>2</sub> and O<sub>2</sub> respectively.  $x_{H_2O}$ ,  $x_{CO_2}$ ,  $x_{N_2}$ ,  $x_{O_2}$  are the corresponding mass fractions of  
574 these species in the exhaust gases.

575 In this study, where the engine is used without the exhaust exchanger, the thermal power of  
576 the CHP is expressed by the thermal power available in the exhaust gas at the engine output. It  
577 is determined using Equation 11.

$$578 \dot{H}_{Exhaust\_Gas} = \dot{m}_{Exhaust\_Gas} * C_{p_{Exhaust\_Gas}} * T_{Exhaust\_Gas} \dots\dots\dots (Eq.11)$$

579 Where  $\dot{m}_{Exhaust\_Gas}$  is the mass flow rates of exhaust gas.  $T_{Exhaust\_Gas}$  is the temperature of  
580 exhaust gases in [°C] just at the outlet of the engine combustion chamber (exhaust manifold).  
581 Simulation results using ANN3 based model led to evaluate the average thermal power  
582 contained in the exhaust gases. Figure 12-b illustrates the evolution of thermal power of exhaust  
583 gases as a function of the engine load and the number of digesters. It shows that the thermal  
584 power available in the exhaust gas is between 5 and 13 kW. Since the thermal power of the  
585 CHP unit is given by the thermal power which is actually recovered, it will be estimated by  
586 multiplying the results of the figure 12-b by the efficiency of the heat exchanger used in the  
587 CHP unit. A similar assumption is already used by Teymoori et al [66] developed a case study  
588 applied to an animal farm, covering the technical and economic aspects of biogas production  
589 using manure from livestock to replace fossil fuel used for heat and electricity generation. They  
590 estimated the thermal power of the CHP plant based on the assumption of constant thermal  
591 efficiency, which is estimated at 65 % of the primary power.

592 For the above cited example where a CHP unit consisting of 5 digesters and an engine  
593 operating under load of 70 % is considered, the thermal power available in the exhaust gas is  
594 about 10 kW. In the field of combined heat and power, the used heat exchangers can recover  
595 up to 60 % of the thermal power contained in the exhaust gases. Indeed, similar percentages  
596 have been obtained experimentally by running an 8 kWe cogeneration unit (ecoGEN-08AH)  
597 [68] in dual fuel operation mode.

598 In summary, based on these assumptions, the 1 kWe micro-CHP unit (shaft power), requiring  
599 a generator with a nominal electric power of 1 kW, can produce up to 2.45 kW of thermal  
600 power.

#### 601 **4. Conclusion**

602 Mico-CHP on farm, where electricity and heat are produced from the anaerobic digestion of  
603 farm effluents, is increasingly the focus of many researchers. Dual-fuel engines are known for  
604 their flexibility in biogas composition, which varies throughout the duration of the anaerobic  
605 digestion reaction. The modeling of the micro-CHP unit operating in dual-fuel mode is carried  
606 out on the basis of experimental results carried out at the laboratory scale. The engine tests were  
607 carried out on an AVL engine with a maximum power of 3.5 kW, operating in dual fuel mode.  
608 The biogas flow rate is evaluated using experimental results from the literature based on  
609 anaerobic co-digestion of mixture of oat straw and cow manure.

610 The engine parameters have been modeled using methodology based on Artificial Neural  
611 Networks. Three ANN based models are developed to estimate engine parameters namely pilot  
612 fuel flow rate, intake airflow rate and the exhaust gas temperature. The inputs of the ANN based  
613 models are engine power, biogas flow rate, and biogas methane content. The ANN based  
614 models have been shown to provide quite satisfactory and acceptable performance. Their  
615 RMSE is between 0.34 % and 0.62 % and their R-squared is between 0.99 and 1. Each of them  
616 consists of two fully connected hidden layers. The ANN1 which models the pilot fuel flow rate  
617 includes five neurons in its first hidden layer and four neurons in its second hidden layer. The  
618 ANN2 which models the airflow rate includes three neurons in its first hidden layer and five  
619 neurons in its second hidden layer. The ANN2 which models the exhaust temperature includes  
620 five neurons in its first hidden layer and three neurons in its second hidden layer.

621 The effect of the number of digesters on the biogas characteristics is studied and the optimal  
622 CHP conception, allowing the use of only 10% of the primary energy from the pilot fuel, is  
623 CHP unit consisting of 5 digesters and dual fuel engine whose a nominal load equal to 70 % of  
624 its maximum load. A micro-CHP unit of 1 kWe, requires a dual fuel generator with a nominal  
625 power of 1 kW, five digesters and a daily availability of effluents of 171 kg / day, consisting of  
626 45 kg/day of oat straw and 126 kg/day of cow manure. It can also recover up to 2.45 kW of  
627 thermal power from the exhaust gases.

628 Works using a truly micro-CHP model, operating in diesel-biogas dual-fuel mode and  
629 equipped with an exhaust exchanger must be carried out. It is necessary to optimize its operation  
630 by acting on two parameters: The first is to improve the efficiency of the engine during  
631 operation in dual fuel mode. Indeed, the lower air-fuel equivalence ratio of diesel engines often  
632 involves unburned methane in the exhaust, which reduces the efficiency of dual-fuel engines.  
633 The second is to optimize the thermal power of the CHP unit by maximizing heat recovery from  
634 the exhaust and the heat recovery from the engine jacket.

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