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A Genetic Algorithm Optimal Schedule of a Single Anaerobic Digester Considering Multiple Feedstocks

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Abstract

As worldwide environmental awareness grow, alternative sources of energy have become important to mitigate climate change. Biogas in particular reduces greenhouse gas emissions that contribute to global warming and has the potential of providing 25% of the annual demand for natural gas in the U.S. In 2011, 55,000 metric tons of methane emissions were reduced and 301 metric tons of carbon dioxide emissions were avoided through the use of biogas alone. Biogas is produced by anaerobic digestion through the fermentation of organic material. It is mainly composed of methane with a rage of 50 to 80% in its concentration. Carbon dioxide covers 20 to 50% and small amounts of hydrogen, carbon monoxide and nitrogen. The biogas production systems are anaerobic digestion facilities and the optimal operation of an anaerobic digester requires the scheduling of all batches from multiple feedstocks during a specific time frame. The availability time, biomass quantities, biogas production rates and storage decay rates must all be considered to maximize biogas production. The scheduling of feedstock in anaerobic digestion facilities would optimize significantly the total biogas production. Therefore, a new genetic algorithm is proposed with the main objective to optimizing sequence and time considering feedstock characteristics for processing. The optimizing algorithm would scrutinize different type of feedstocks, arrival times and decay rates, as all batches are individually processed in the digester.

Keywords
Genetic Algorithm, Job scheduling optimization, Anaerobic digester, Renewable energy.

1. Introduction
Several environmental benefits derived from the production and utilization of biogas obtained from anaerobic digestion can be obtained. Its production helps avoid greenhouse gas emissions such as methane and nitrous oxide, which contribute to climate change, which would otherwise be directly released to the atmosphere by natural decomposition of biomass. Moreover, it reduces carbon dioxide emissions by offsetting conventional fossil fuels such as lignite, coal, oil and natural gas. According to the Environmental Protection Agency in 2011, around 541 million kilowatt-hours (kWh) of usable energy were produced in the U. S. by digester systems. Using the U.S. EPA's 2011 LFGE Benefits Calculator, this amount of energy can supply over 36,000 average U. S. homes for a year. Furthermore, 55,000 metric tons of methane emissions were reduced and 301,000 metric tons of carbon dioxide emissions were avoided by offsetting fossil fuels. The U. S. EPA's Greenhouse Gas Equivalencies Calculator indicates that these reduced emissions are equivalent to removing 294,000 vehicles from the road, reducing the oil consumption by nearly 3.5 million barrels, or reducing the gasoline consumption by more than 168 million gallons.

Among other benefits, the biogas produced by anaerobic digesters can be used to generate energy with 41% electrical efficiency. It can also be used as a vehicle fuel with greater efficiency and reduce 95% of carbon dioxide emissions. However, the biogas production process may not necessarily be as economically attractive on a large industrial scale as other biofuels. Therefore, the optimization of anaerobic digesters process is essential to enhance the productivity of these systems. Mathematical models can be used to maximize biogas production in anaerobic digester systems.

2. Literature review

Anaerobic digestion was modeled and optimized using a response surface methodology [8] and artificial neural networks [1, 13]. Fakharudin structured the response surface methodology (RSM) with two training approaches to feed a set of neural network design to generate maximum biogas output. Their results demonstrated a 0.44% increase of the maximum biogas using the RSM [8]. Abu [1] applied an Artificial Neural Network (ANN) and Genetic Algorithm (GA) to simulate and optimize the digester's biogas production process from a biogas plant. The ANN model, using operational plant data from a period of 177 days, was trained to simulate the digester operation incorporating the effect of digester parameters, (e.g. temperature, non-volatile solids and volatile solids, and pH on the biogas yield). The GA optimized and predicted the methane production with a 0.87 correlation coefficient of effectiveness. After finding the optimal operating conditions through the model the methane production increased by 6.9 %. Gueguim [13] developed an Artificial Neural Network (ANN) to model the biogas production on mixed substrates of saw dust, cow dung, banana stem, rice bran and paper waste. The model's process was optimized using a Genetic Algorithm (GA) and the model was the fitness function. The data used to train and validate the ANN model were taken from twenty five mini-plot biogas fermentations. A predicted biogas performance of 10.144L was provided using the optimized substrate profile while its evolution gave a biogas production of 10.280L increasing its performance by 8.64%. Balmant [2] analyzed the optimal residence time and substrate input mass flow rate to maximize the production of methane in anaerobic digestion. A numerical simulation was performed with a general transient mathematical model of an anaerobic biodigester. The steps considered for the model were: acidogenesis, acetogenesis and methanogenesis for well mixed reactors. Their model assesses the transient and steady state behavior as operating conditions and biodigester designs change. A parametric analysis proved that biogas production strongly depends on the polymeric substrate's input and fermentable monomer concentrations, but quite independent of the propionic's input, butyric and acetic acid concentrations. The optimal residence time and substrate input mass flow rate were found by conducting an optimization study and the results showed a sudden dropped of methane from the observed maximum zero, within a 20% range around the optimal operating parameters.

One could focus on the optimal batch schedules and residence times in anaerobic digesters to maximize the total gas production. For instance, Curry [6] considered the problem of scheduling both single and multiple feedstocks in a single digester system. The parameters considered to evaluate biogas production include: availability time, biomass quantities, biogas production rates, storage decay and the feedstock decay while in storage. A dynamic programming algorithm was used to solve the single feedstock batch scheduling problem while a decomposition approach was employed to solve the multiple feedstock problem. Deuermeyer [7] introduced a perishable inventory and production problem related to the production of biogas via anaerobic digestion with a fixed capacity. A numerical algorithm optimized the total gas production over a fixed planed horizon. The problem was to determine the optimal residence times for batches in the anaerobic digester considering the biomass decay while in storage.
Feldman [10] proposed a dynamic programming to solve the scheduling of two different types of feedstocks with decreasing production rates. The objective was to maximize the total gas production in a facility with limited capacity. Two decision variables were considered; the optimal residence times in the digester for both feedstocks and the amount of time the production facility used for digesting the feedstocks. Gim [11] presented a branch and bound algorithm to solve the scheduling of a single anaerobic digester with multiple feedstocks. The batch production sequence and residence times determined the total gas production over a specific time frame. The declining viability of stored biomass was considered.

3. Model description

The scheduling sequence of feedstocks and their processing time allocated in the single anaerobic digester will determine the total production of biogas. To calculate the unit gas production of each feedstock given the batch residence time t, the gas production function form of Chynoweth [3] was employed.

$$g_i(t) = \alpha_i\left(1 - e^{(-\beta_i[t-d]^+)}\right) \tag{1}$$

The rate ($g_i(t)$) is a function of time where the biomass-gas conversion coefficients of feedstock i are given by α_i and β_i. The setup time, d, is included in the batch residence time, therefore the net batch residence time is given by $t - d$. Also, $[t-d]^+$ indicates that only positive values can be considered since there cannot be negative days. Therefore, the maximum of 0 and $t - d$ is taken. It is assumed that the batches of the same feedstock are homogeneous in the digester and that the environment is reasonably constant to keep $g_i(t)$ from varying over time.

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The biomass decomposition occurring in storage would also ultimately affect the gas production. Since only one batch can be process at a time, the stored bathes react with air as they wait for processing. During this period, any stored batch will suffer a declined efficiency that will directly affect its biogas yield. To calculate the decay of each feedstock with respect to the storage time, a decay factor is estimated using the following equation

$$h_i(s) = e^{-\gamma_i s} \tag{2}$$

In equation 2, s is the storage time until the batch is processed in the digester and $\gamma_i$is the storage decay factor of feedstock i. The actual gas yield of a batch from feedstock *i* that was stored *s* amount of time and whose residence time in the digester is *t* time units is given by the product of the unit gas production and the decay function

$$\alpha_i\left(1 - e^{\left(-\beta_i[t-d]^+\right)}\right) \cdot e^{-\gamma_i s} \tag{3}$$

To estimate the total gas produced by the anaerobic digester considering different types of feedstocks and arrival times the following mathematical procedure presented by Gim[11] is used in the present work. In this procedure, the different feedstocks are arranged in increasing order according to their arrival times, assuming that the arrival time for the first feedstock equals to zero, therefore $r_1 = 0$ and $r_i \leq r_j$if $i < j$. The decision variable $x_{ij} = 1$ specifies the multiple feedstocks with i being the feedstock type and j the batch number for the denoted feedstock and 0 otherwise and the batch residence time which is represented as t_j for *j* = 1, 2, …., n.

A batch is considered a candidate for the *j*th position if its arrival time (r_i) is less than or equal to its start time, $\sum_{k=1}^{j-1} t_k$. The storage time for the *j*th batch includes the setup time *d* as the decay also occurs during this process, thus$\sum_{k=1}^{j-1} t_k + d - r_i$. Hence, the biogas production of the *j*th batch from feedstock type *i* is expressed as follows.

$$f_{ij}(t_j) = \begin{cases} h_i\left(\sum_{k=1}^{j-1} t_k + d - r_i\right) g_i(t_j) \text{if} \sum_{k=1}^{j-1} t_k \geq r_i \\ \\ 0 \text{ otherwise} \end{cases} \tag{4}$$

The objective function: Maximize $\sum_{i=1}^{m} \sum_{j=1}^{n} f_{ij}(t_j) x_{ij}$

Subject to:

$$\sum_{j=1}^{n} t_j = T, \tag{5}$$

$$\sum_{i=1}^{m} x_{ij} = 1, \text{for} j = 1, 2, \dots, n, \tag{6}$$

$$\sum_{j=1}^{n} x_{ij} = n_i, \text{for} i = 1, 2, \dots, m, \tag{7}$$

$$t_j \geq 0, \qquad \text{for} j = 1, 2, \dots, n, \tag{8}$$

$$x_{ij} = 0 \text{ or } 1, \text{for all} i \text{and} j \tag{9}$$

Where *m* = the number of feedstocks, $n_i =$ the number of batches in feedstock *i*, for *i* = 1, 2, …,*m*, *n* = the total number of batches and T = the planning time horizon. The first constraint accounts for the total time available. The second constraint indicates that only one batch can be processed at a time. The third constraint specifies that all batches are eventually processed. The fourth constraint denotes the residence time of the feedstock. Finally, the fifth constraint indicates the multiple feedstock type.

4. Model Development

The Genetic Algorithm (GA) is a search heuristic based on the Darwinian theory of evolution. It was first proposed by John Holland in 1975 and later developed by Goldberg in 1989 and is generally used to solve optimization problems [16]. It has been applied in complex problems in many different fields. For instance, the designing a sliding mode control system [17], robot trajectory planning [19], adapting IIR filters [18], low cost design of IIR digital filters [20], design of robust control systems [12], tracking changing environments [4], solving the k-partition problem on hyper cubes [5], job shop scheduling, rescheduling and open shop scheduling problems [9], simultaneous design of membership functions and rule sets for fuzzy controllers [14], pump scheduling for water supply [15], among many others. In the present study, a GA was developed to determine the optimal scheduling of a single anaerobic digester considering multiple feedstocks with different arrival in order to maximize biogas production. The steps of the algorithm are as follows.

- Encoding: The individual's chromosomes include the feedstock sequence and their corresponding residence times as seen in figure 1. The first section of the chromosome belongs to the batch sequence which is generated based on the number of batches indicated. The second half of the chromosome correspond to the residence's time of the batches in the same order with the restriction that its sum is equal to time allowed to process all the batches.

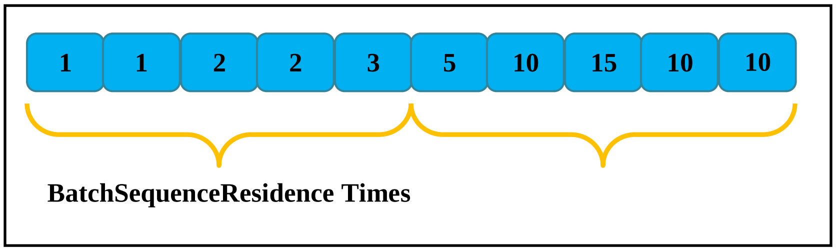

Figure 1: Chromosome

- Initialization: The individuals are randomly generated to form the initial population and each contains a possible solution to the problem.
- Evaluation: The entire initial population is evaluated according to the fitness function, in this case, the gas production formula previously mentioned.

$$f_{ij}(t_j) = \begin{cases} h_i\left(\sum_{k=1}^{j-1} t_k + d - r_i\right) g_i(t_j) & \text{if} \sum_{k=1}^{j-1} t_k \geq r_i \\ 0 \text{ otherwise} \end{cases} \tag{10}$$

After that, the individuals are correspondingly to their fitness value in descending order.

- Selection: The elite parents are chosen from the best fitted individuals using an elitism rate to pass intact to the next generation. The remaining spots are filled by the tournament selection method considering the entire population. Tournaments are played between two random individuals and the one with the highest gas production is chosen to be parent number 1. Another pair of random individuals is selected and the same criterion is used to select parent number 2.
- Reproduction: Once the parents are selected they have a specified probability (crossover rate) of being reproduced. Because the order of the chromosome matter a direct swap is not possible. Therefore, if the parents reproduce, the chromosome is split into two and two different single point crossovers are applied to each side to create two children.

The first point crossover is applied to the batch sequence where the first two columns of "parent 1" and the last three from "parent 2" are taken and create the batch sequence for "child 1". Also, the first two columns of "parent 2" and the last three from "parent 1" are taken and create the batch sequence for "child 2". Similarly, the second point crossover is applied to the residence times where the first two columns of "parent 1" and the last three from "parent 2" create the residence times for "child 1" and the first two columns of "parent 2" and the last three from "parent 1" create the residence times for "child 2". Figure 2 shows this procedure.

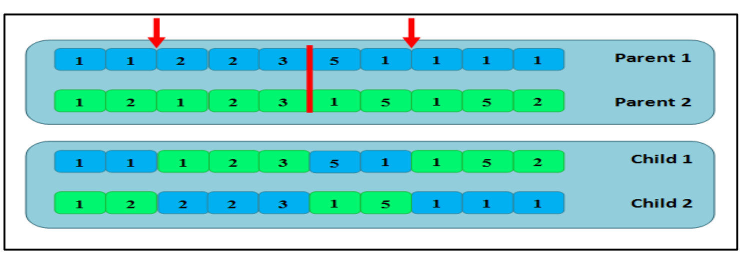

Figure 2: First Crossover

Then another set of single point crossovers are applied again to create two more children. This time the first crossover point includes the first three columns from "parent 1" and the last two from "parent 2" to create the batch sequence for "child 3". Also, the first three columns from "parent 2" and the last two from "parent 1" create the batch sequence for "child 4". Similarly the second crossover is applied to the residence time where the first three columns from "parent 1" and the last two from "parent 2" create the residence times for "child 3" and the first three columns from "parent 2" and the last two from "parent 1" create the residence times for "child 4". Figure 3 shows this procedure.

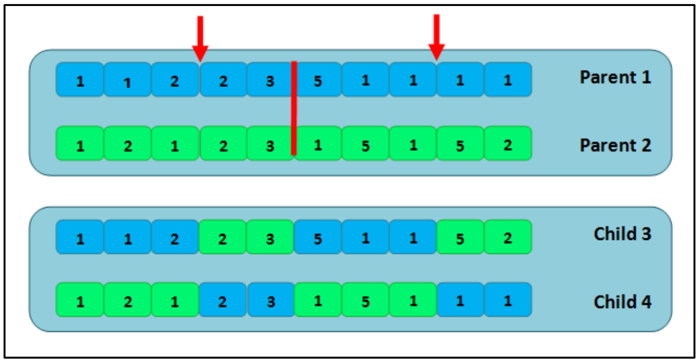

Figure 3: Second Crossover

In addition, once the four children are created they have a specified probability of being mutated (mutation rate) which can only be applied to one side of the chromosome or the other. If mutation is applied, two random points that belong to the same side are swapped. In figure 4, the mutation was applied randomly to the batch's sequence. However, the mutation can also be applied to the residence times if the two random points lay on the second half of the chromosome

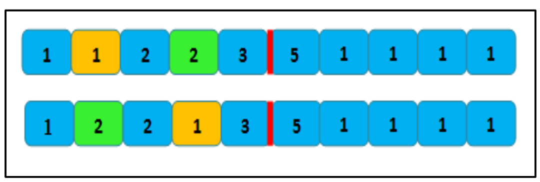

Figure 4: Mutation

- Stopping criterion: The algorithm stops after a specific number of generations and the optimal solution is given by the individual with maximum gas production in the last generation. On the other hand, if the optimal solutions between generations increment by less than an specified epsilon rate then, the algorithm stops and the optimal solution for the problem is given by its last generation.

5. Case Studies

5.1 Case Study 1

An example problem taken from Gim [11] was used to solve the scheduling of a single anaerobic digester with multiple feedstocks. The problem considers three different types of feedstocks (i) with one or two batches (n_i) and different arrival times (r_i). All batches need to be processed in the digester in a time period of 50 days with the restriction that only one batch can be processed at a time. The batch set up time d is one day. The feedstock parameters are shown in the table 1 below.

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Table 1: Feedstock Parameters Case Study 1

Feedstock	$g_i(t)$		$h_i(s)$	Arrival times	Batches
i	α_i	β_i	γ_i	r_i	n_i
1	28	0.1	0.021	0	2
2	13.2	0.09	0.015	15	2
3	18	0.12	0.02	25	1

The multiple feedstock scheduling of problems was solved using the Genetic Algorithm described which was coded in Matlab®. The optimal solution given in the first run was < 1 1 3 2 2 10 15 15 5 5 > with a total gas production of 52.5787. After running the program different times the same optimal sequence < 1 1 3 2 2 > is obtained but the residence times are different with each run, making the solution vary slightly. The total computational time was 3.56 seconds using an Acer computer with a processor Intel® Celeron® CPU 900 @ 2.20 GHz 2.19 GHz.

5.2 Case Study 2

To compute different problems and test the ability of the programmed GA the same problem was considered increasing the number of batches for each feedstock. The rest of the parameters, both the GA's and the problems', where kept the same. Table 2 show the new set of batches for each feedstock type. The optimal sequence for this example problem using the GA described is <1 1 1 3 3 2 2 2> with residence times <5 10 10 5 5 5 5 5> respectively.

Table 2: Feedstock Parameters Case Study 2

Feedstock	$g_i(t)$		$h_i(s)$	Arrival times	Batches
i	α_i	β_i	γ_i	r_i	n_i
1	28	0.1	0.021	0	3
2	13.2	0.09	0.015	15	3
3	18	0.12	0.02	25	2

5.3 Case Study 3

Another example that includes more feedstocks was also solved. The time to process all the batches (T) was changed to 130 days, the population size was increased to 100 individuals and the number of generations to 150 while the rest of the GA's parameters were kept the same. The problem's parameters α, β, γ, r and n are shown in table 3. The optimal sequence found is <1 2 5 4 3 6 6 6 7 3 1 7> with residence times <30 30 10 5 5 5 5 10 5 5 5 15> achieving a total gas production of 119.8115.

Table 3: Feedstock Parameters Case Study 3

Feedstock	$g_i(t)$		$h_i(s)$	Arrival times	Batches
i	α_i	β_i	γ_i	r_i	n_i
1	20	0.1	0.015	0	2
2	28	0.08	0.018	30	1
3	15	0.13	0.021	45	2
4	13	0.21	0.019	50	1
5	25	0.09	0.025	60	1
6	18	0.2	0.02	80	3
7	21	0.11	0.011	100	2

6. Sensitivity Analysis

It is important to study the effect of the GA's parameters on the optimal solutions because real answer for the problem is unknown; therefore the solution is estimated as best as possible. For this reason, a sensitivity analysis was done to evaluate different parameters. The parameters considered for the analysis are: Population size, number of generations, elitism, crossover and mutation.

The parameters considered initially where:

- Population size = 50
- Number of generations = 20
- Elitism = 25%
- Crossover = 75%
- Mutation = 1%

The Population size was increased by five to have a bigger range of solutions and increase the probability of finding best fitted individuals. The number of generations was also increased by fives in every analysis to give the algorithm a better opportunity to evolve and explore different solutions. Elitism was increased by 1% to keep the best fitted individuals in subsequent generations and to evaluate its impact. Finally, mutation was also increased by 1% to see if by altering the chromosomes the results improve or worsen.
The sensitivity analysis was performed to evaluate both the computational time of the program and the maximum gas production. Table 4 shows the results of the analysis. It was observed that the maximum gas production obtained was the same from generation 60 through 90, although the computational time varied every time. Using the minimum computational time as a decision criteria, the optimal solution is given when the parameters are equal to population size 60, generations 30, elitism 27%, crossover 77% and mutation 1.2% with a maximum gas production of 52.57877 and a computational time of 3.152 seconds.

Table 4: Sensitivity analysis-five days' increments.

MTB	Population Size	generations	Elite	Crossover %	Mutation %	Computational Time	Maximum Gas Production	Generation
5	50	20	0.25	75	1	2.666 s	52.54054322	20
5	55	25	0.26	76	1.1	2.800 s	52.54054322	12
5	60	30	0.27	77	1.2	3.152 s	52.57877749	24
5	65	35	0.28	78	1.3	3.428 s	52.57877749	16
5	70	40	0.29	79	1.4	3.674 s	52.57877749	33
5	75	45	0.3	80	1.5	4.057 s	52.57877749	11
5	80	50	0.31	81	1.6	4.325 s	52.57877749	17
5	85	55	0.32	82	1.7	3.591 s	52.57877749	21
5	90	60	0.33	83	1.8	5.129 s	52.57877749	10
5	95	65	0.34	84	1.9	5.570 s	52.54054322	21
5	100	70	0.35	85	2	6.165 s	52.54054322	23

Because the original problem was solved using increments of fives for the residence times another sensitivity analysis was performed exploring all possible days. The reason for this was to explore different solutions and give a bigger range of possible times. The same parameters described were analyzed and table 5 shows the results. The maximum gas production is obtained when the parameters are equal to population size 90, generations 60, elitism 33%, crossover 83% and mutation 1.8% yielding 53.0663 of gas with a computational time of 5.767 seconds.

Table 5: Sensitivity analysis-one day increment.

MTB	Population Size	generations	Elite	Crossover %	Mutation %	Computational Time	Maximum Gas Production	Generation
1	50	20	0.25	75	1	2.605 s	52.27409246	7
1	55	25	0.26	76	1.1	2.848 s	52.65022698	12
1	60	30	0.27	77	1.2	3.726 s	52.54996795	26
1	65	35	0.28	78	1.3	3.621 s	52.74557102	30
1	70	40	0.29	79	1.4	4.059 s	52.82949091	19
1	75	45	0.3	80	1.5	4.436 s	53.06440505	42
1	80	50	0.31	81	1.6	4.531 s	52.55578988	41
1	85	55	0.32	82	1.7	5.437 s	52.54516956	37
1	90	60	0.33	83	1.8	5.767 s	53.06634228	41
1	95	65	0.34	84	1.9	6.187 s	52.54516956	26
1	100	70	0.35	85	2	7.068 s	52.86893156	70

7. Conclusions

The Genetic Algorithm proposed solves the scheduling problem of one anaerobic digester when multiple feedstocks arrive at different times in order to maximize its total gas production. The extreme advantage of using a genetic algorithm to optimize the processing of biomass to produce methane gas was explained. The core of the genetic algorithm incorporates both the batch sequence as well as the processing time for each batch. The number of batches and the processing time of the biomass would be augmented with the incorporation of the new code developed in Matlab. Biogas is a significant renewable energy resource that helps reduce greenhouse gas emissions such as methane and nitrous dioxide which contribute to global warming. In addition, biogas has the potential to supply 25% of the natural gas demand in the US. Nevertheless, the economic feasibility to produce this gas depends on the ability to manage anaerobic digesters in a cost effective way. A good way to make these systems viable is by maximizing their gas production through the optimization of their feedstocks' scheduling. The proposed model offered the best solution for the problem of scheduling multiple feedstocks into a single anaerobic digester with a fixed capacity. For future research, the solutions presented can be compared to other optimization algorithms that can also be applied to solve this scheduling problem. Furthermore, this work can be expanded to explore other objective functions, for instance, the integration of more anaerobic digesters with different capacity levels.

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Biography

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