Biogas Plant Control and Optimization Using Computational Intelligence Methods

Biogasanlagenregelung und -optimierung mit Computational Intelligence Methoden

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Summary The optimization of agricultural and industrial biogas plants with respect to external influences and various process disturbances is essential for efficient plant operation. The fact that most biogas plants are manually operated because of a lack of online-measurements and limited knowledge about the anaerobic digestion process makes it necessary to develop new optimization and control strategies. However, the optimization and control of such plants is a challenging problem due to the underlying highly nonlinear and complex digestion processes. One approach to address this challenge is to exploit the flexibility and power of computational intelligence (CI) methods such as Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO). The use of CI methods in conjunction with a validated plant simulation model, based on the Anaerobic Digestion Model No. 1, allows optimization of the substrate feed mix, a key factor in stable and efficient biogas production. Results show that an improvement of up to 20% in biogas production and substrate reduction can be achieved when compared to conventional manual operation. ►►► **Zusammenfassung** Die Optimierung landwirtschaftlicher und industrieller Biogasanlagen kompensiert den Einfluss von internen und externen Prozessstörungen und ermöglicht einen effizienten Anlagenbetrieb. Die meisten Biogasanlagen werden heute noch aufgrund von fehlender Online-Messtechnik und wegen begrenztem Fachwissen über den anaeroben Faulungsprozess von Hand gefahren. Der Einsatz neuer Optimierungs- und Regelungsstrategien eröffnet dem Betreiber wertvolle und ertragssteigernde Perspektiven. Allerdings ist die Optimierung und Regelung solcher Anlagen wegen der hochgradig nichtlinearen und komplexen Faulungsprozesse eine besondere Herausforderung. Die Flexibilität und Intelligenz von Computational Intelligence (CI) Methoden, wie z. B. Genetischen Algorithmen (GA) und der Particle Swarm Optimization (PSO) qualifizieren diese Verfahren zu geeigneten Lösungswerkzeugen. Dies, in Verbindung mit einem validierten Anlagensimulationsmodell, basierend auf dem Anaerobic Digestion Model No. 1, erlaubt die Optimierung der Mischungsverhältnisse bei der Substratzufuhr, welche einer der wichtigsten Schlüssel für eine stabile und effiziente Biogasproduktion ist. Die Ergebnisse zeigen, dass im Vergleich zur konventionellen manuellen Fahrweise eine Verbesserung von bis zu 20% in Bezug auf Biogasproduktion und Substrateinsparung erreicht werden kann.

Keywords Biogas plants, optimization, control, Computational Intelligence ►►► **Schlagwörter** Biogasanlagen, Optimierung, Regelung, Computational Intelligence Methoden

1 Introduction

In the past twenty years the rise in worldwide energy production using the conversion of biomass materials to methane in biogas plants has its origin in large-scale government aid. Renewable energy laws guaranteeing lucrative electricity remuneration rates and funding for biogas plant construction, support a growing biogas sector [1; 2].

This new market for renewable energy from energy crops and municipal organic waste is struggling in Germany due to reducing governmental support and rising prices for biomass, which is considered to be one of the biggest problems. In addition to that, costs for transportation and disposal of fully fermented biomass have an additional negative impact on biogas plant operation. Furthermore, the global economic downturn and fluctuating prices for energy from fossil fuels, make it difficult for biogas plants to remain competitive in the long run. Efficient plant operation is therefore crucial to ensure that biogas companies remain viable. The use of advanced control and optimization systems for biogas plants offers a suitable and cost-effective solution to increase biogas production and guarantee stable process conditions. However, detailed knowledge of anaerobic digestion processes is a necessary prerequisite for implementing this solution. Fortunately this is becoming increasingly attainable due to recent developments in online-measurement and process monitoring systems.

The difficulties with biogas plant operation are primarily due to the complexity of anaerobic digestion processes. Physical, chemical and biological processes run simultaneously and are furthermore affected by external influences such as local weather conditions, environmental changes and changes in daily feed load. The combination of multiple complex processes and their dependencies on external influences make it difficult to develop an automated control and optimization strategy which is both reliable and effective. Reliability is of particular importance for agricultural biogas plants, where permanent attention and supervision by an operator is not practical.

To develop such an optimal control strategy, it is critical to monitor anaerobic digestion processes as closely and accurately as possible to enable estimation of process states and to detect unstable process states in time and if possible in advance. This facilitates the implementation of more effective control measures. Online process monitoring is rare at most agricultural and even some industrial biogas plants because of high acquisition and maintenance costs and a lack of reliability during *in situ* measurements as proven by Kujawski *et al.* (2007) [3]. This necessitates the development of new methods for designing and optimizing advanced control strategies before testing them in practice. One common approach is to use pilot- or lab-scale anaerobic digestion reactors which are equipped with extensive laboratory and online-measurements to test new control and optimization strategies [4]. A second approach is to use dynamic simulation models for anaerobic digestion [5]. In addition to the associated cost, a major disadvantage of using pilot-scale reactors to validate control and optimisation strategies is that the dynamic behaviour of small reactors does not always scale to full-scale reactors due to the highly nonlinear nature of these systems. Given these deficiencies this article focuses on the benefits of using full-scale plant simulation models for the validation of control and optimization systems.

This article introduces the use of Genetic Algorithms and Particle Swarm Optimization to optimize biogas plant operation using a dynamic simulation model for anaerobic digestion, the Anaerobic Digestion Model No. 1 (ADM1) [6]. In particular, the substrate feed (total amount and mixture) is optimized, taking into account constraints such as amount of total solids and digester load. The flexibility of these computational intelligence (CI) methods makes them perfectly suited to the non-convex multi-objective nature of the optimisation problems posed by these complex systems.

Section 2 gives a short review of the current state of the biogas market in Germany while Sect. 3 describes the functionality of biogas plants and the main anaerobic digestion processes involved, as well as the commonly used control and optimization strategies. Newly developed sensor technologies that can provide the online-measurement needed for optimization and control, are introduced in Sect. 4. The full-scale simulation model of the biogas plant and the CI methods employed to optimise biogas plant parameters are then introduced in Sects. 5 and 6, respectively. Furthermore, Sect. 6 summarises the results achieved for a biogas plant substrate feed optimisation case study and gives a final evaluation of the optimization strategies considered. Finally, future opportunities in biogas plant operation and control are highlighted.

2 Situation in Germany

The biogas market in Germany was booming in the last decade due to the Renewable Energy Sources Act from 1999 and the amended version from 2004 as can be seen in Fig. 1.

In spite of the steadily increasing number of biogas plants, it becomes more and more difficult to assure sustained efficient plant operation. Rising prices for available biomass which are caused by an increasing demand

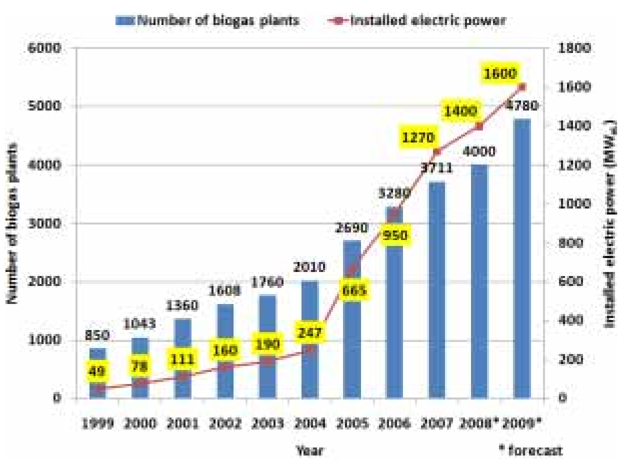

Figure 1 Development of the number of biogas plants and the overall installed electric power in Germany [7].

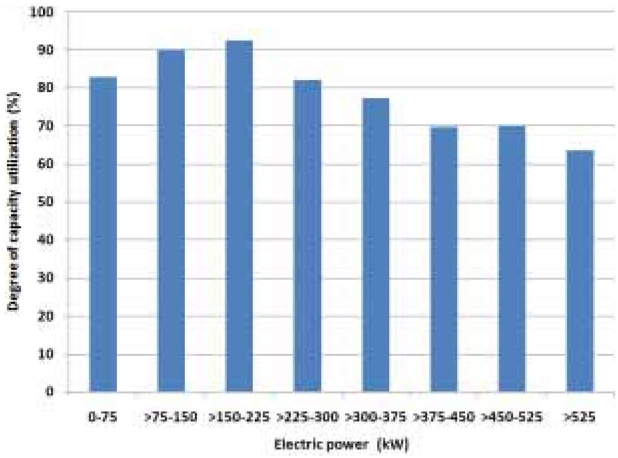

Figure 2 Comparison of the degree of capacity utilization of 70 biogas plants [8].

force operating companies to improve process efficiency in terms of higher biogas production and quality. In addition, increasing costs for energy, construction, maintenance and process monitoring of biogas plants on the one hand, and steadily reducing remuneration rates on the other hand, put pressure on an already struggling market.

The positive effects the Renewable Energy Sources Act has had so far on the biogas market are not going to last indefinitely. Even the new amended version, coming in 2009, will not be able to stop obvious consolidation in the biogas sector. However, the promotion of smaller so-called "farmyard biogas plants" and higher remuneration rates for efficient waste heat recovery at biogas plants starting from January 2009 support new ideas and developments.

Taking into consideration current developments in the biogas sector, intelligent, efficient control and optimization systems are needed more than ever to improve plant operation and thus plant efficiency. Figure 2 clearly indicates that larger biogas plants (with an energy production above 300 kW), in particular, suffer from inefficient plant operation. More than 30% of the plants true potential remains unused. The reasons are obvious. The bigger the size of the biogas plant, the more substrate is needed to achieve efficient operation, which often is not available or expensive due to high costs for transport and logistics. In particular, the return transport of fully-fermented biomass is time-consuming and expensive. Further, the disposal of fully-degraded biomass from bigger biogas plants requires an appropriate area of cultivation, whose availability is limited. Moreover, physico-chemical processes behave in a completely different fashion in small fermentation tanks compared to large tanks, due to differences in sedimentation and the circulation of currents in the tanks.

3 Biogas Plant Operating Principles

Biogas plants are designed to produce methane (CH_4) and carbon dioxide (CO_2) from organic material in the absence of oxygen. This conversion is called anaerobic digestion and its end-product is biogas. While there are big differences between the scale and operation of industrial and agricultural biogas plants, the basic plant design and components are essentially the same in most cases. Each biogas plant consists of one or several storage tanks for organic material, a fermentation tank and a final storage tank for fully digested sludge as shown in Fig. 3.

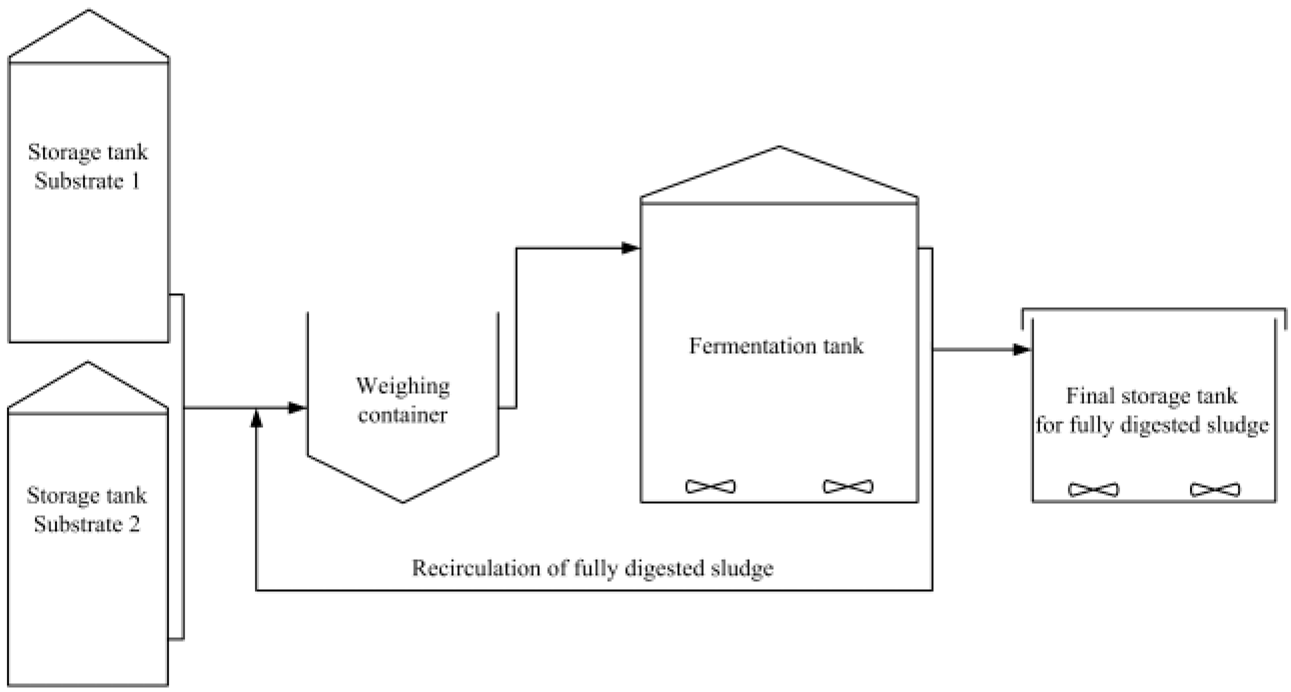

Figure 3 General layout of a Biogas plant.

The fermentation tank has two phases, a gas and a liquid phase where organic material is digested by anaerobic bacteria in a relatively complex bio-chemical process. There are four processes involved in biogas production [9].

1. *Hydrolysis* breaks complex organic structures open to make them accessible to the following processes.
2. *Acidogenesis* produces organic acids as well as hydrogen, carbon dioxide, different alcohols and a small amount of acetic acid out of organic material.
3. *Acetogenesis* uses organic acids, hydrogen and carbon dioxide to produce acetic acid.
4. *Methanogenesis* produces methane from acetic acid and to a lesser extent from hydrogen and carbon dioxide.

All processes involved in anaerobic digestion make different demands on pH-value and concentration of organic acids and they further rely on the full functionality of the other processes. This sensitive balance between the simultaneously running fermentation processes is difficult to maintain.

In practice, as illustrated in Figs. 4 and 5, variations in the throughput of substrate and concentration of organic total solids (oTS) in the substrate are the main factors that influence process stability and biogas production in agricultural biogas plants. The efficient optimization and control of these plants can therefore be realized by adapting the substrate feed according to the state of anaerobic digestion. Currently, mainly two main strategies for biogas plant operation are used [10]:

Low substrate feed. The total amount of substrate fed to a biogas plant is reduced to assure enough buffer capacity against disturbances in the fermentation tank. Hence, biogas production and plant efficiency decrease.

High substrate feed. The total amount of substrate fed to a biogas plant is increased to achieve maximum biogas production and plant efficiency. A sophisticated control system with expensive online measurement systems is crucial to maintain process stability.

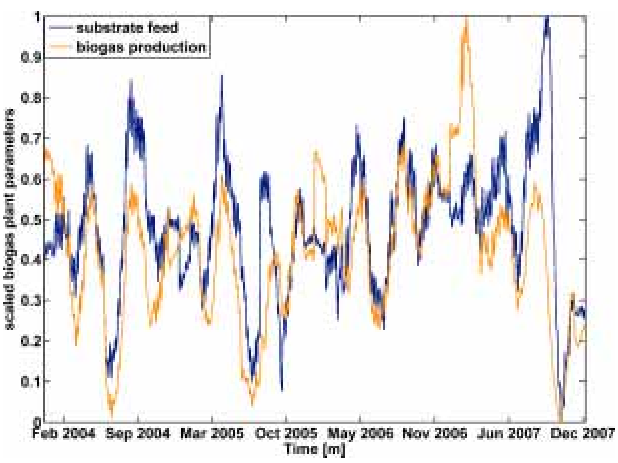

Figure 4 Development of biogas production against total substrate feed from 2004 to 2007 of a full-scale biogas plant.

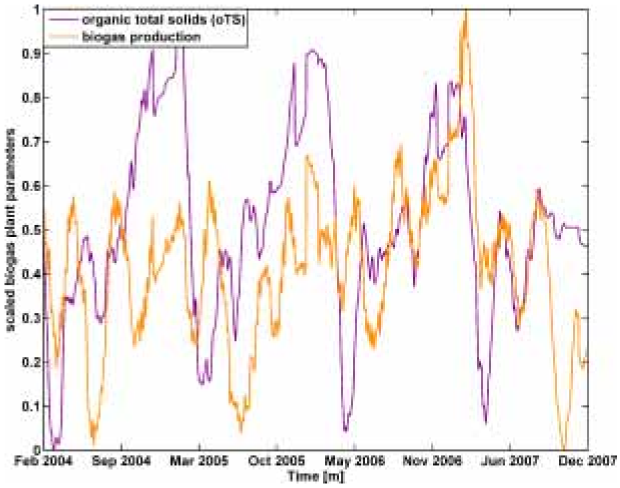

Figure 5 Development of biogas production against concentration of organic total solids from 2004 to 2007 of a full-scale biogas plant.

Agricultural biogas plants, in particular, are generally operated at low substrate feeds, as advanced control and measurement systems are not feasible. However, the advent of new cheaper online-measurement technologies coupled with the recent development of dynamic biogas simulation models, makes agricultural biogas plant optimization and control possible.

3.1 Common Control and Optimization Strategies

Better control and optimization of the anaerobic digestion process is one of the most effective ways of improving the efficiency of biogas power plants, but other approaches can also be used to improve plant operation. These include control of the cogeneration units with respect to variations in biogas amount and quality and the optimization of stirring intervals for the agitators inside the fermentation tank to maximise biogas production.

Stirring of the contents of the fermentation tank is very important, because it improves the contact between anaerobic bacteria and available substrate. Moreover, stirring on a regular basis helps to reduce sedimentation and improves homogeneity inside the fermentation tank. Nevertheless continuous strong stirring can also have a negative affect on the speed of anaerobic digestion as increasing shearing forces aggravate the contact between bacteria and substrate. The relationship between stirring and anaerobic digestion processes has been studied in various research projects; see for example [11; 12].

Another way to monitor and improve plant operation is to perform laboratory analysis of the fermentation sludge and substrate feed on a regular basis. Organic acids, ammonium and heavy metal concentrations are the most important parameters that need to be examined. Knowledge of these parameters allows efficient process operating conditions to be determined. However, performing the analysis and interpreting the results requires detailed knowledge about the fermentation process, and access to such expertise is generally only cost effective for the largest biogas production facilities.

Furthermore, while the high level of detail obtained by a laboratory analysis allows a very precise assessment of the state of the process, the analysis of samples generally takes a few days, so that the information is not available in a timely fashion. Clearly this is not satisfactory for the detection of critical process states requiring immediate attention.

These basic control and optimization strategies using PI or PID controllers for temperature and combustion control as well as regularly laboratory analysis, have proven to be efficient and have made a significant contribution to improved biogas plant operation. Nevertheless, new technologies and optimization strategies that take into account new online-measurements, offer new possibilities for faster and more efficient reactions to varying process states. Some developments in this area have already been demonstrated in lab-scale applications and simulation case-studies by Genovesi [13] and Alferes [14].

4 Online-Measurements

The strong progress and decreasing costs in the Automation and IT sector make it possible to broaden the application of online measurement equipment on biogas plants. This is of considerable benefit to operators, as the provision of up-to-date information on process states allows them to make better decisions based on more information, and hence increases the likelihood that plants are operated efficiently.

In addition, available measurement data can be used to develop computer based simulation and optimization models which allow a further increase in productivity with minimum effort for the operator. In the following sections the most common and most interesting parameters that are currently measured on biogas plants are described. Additionally, some interesting and promising new measurement techniques that are currently the subject of research for the biogas sector are introduced briefly.

4.1 Common Online-Measurements

Every biogas plant has a certain number of online-measurement devices that are used to monitor the most critical process parameters. However, the number and quality of the equipment used depend on planned investment volume and regular maintenance.

Table 1 gives a short survey of the most common online-measurements that can be found at most biogas plants.

Monitoring of the fermentation temperature is crucial as methane forming bacteria only survive in relatively narrow temperature bands. Thus, it is necessary to have a reliable value of this parameter at all time. This also applies for redoxpotential, which is used to monitor the anaerobic environment necessary for biogas production (around –500 mV). Very small amounts of oxygen directly result in an increase in redoxpotential.

Table 1 Common online-measurements at biogas plants.

Online-measurement	Application
Temperature	Monitoring of fermentation temperature
Redoxpotential	Monitoring of anaerobic environment
Gas flow	Analysis of gas amount produced
Gas analysis CH_4, CO_2, O_2, H_2S	Monitoring of gas quality, gas composition

To effectively control cogeneration units input biogas flow and composition have to be monitored closely. The biogas composition, in particular, is very important. The concentration of CH_4 in biogas has to be above 50% most of the time to guarantee continuous efficient operation of cogeneration units. Furthermore, high concentrations of H_2S in the biogas can inhibit anaerobic digestion processes as well as cause severe emission- and corrosion-problems in cogeneration units. However, no precise limit values can be specified for H_2S concentrations, because the inhibition depends on the adaptation of the process to H_2S.

4.2 Innovative Online-Measurements

Anaerobic digestion processes are still considered as black boxes [15]. Many important process parameters can only be measured using complex and expensive laboratory equipment. Nevertheless, online-measurement sensors have recently come on the market that can indirectly measure parameters such as organic acids and the amount of total solids. These new sensors are very promising but still need to be validated in long-term operation. In particular, the calibration of these sensors is very complicated and requires expert knowledge.

The measurement of total and organic solids is used to determine the quality of the substrate feed, its potential for biogas production and, if measured inside the fermentation tank, digester load. The more digestible biomass a substrate contains, the higher the amount of organic solids. In agricultural biogas plants that primarily use renewable energy crops, there is only a small difference between total solids and organic solids. With total and organic solids it is common, to use a drying closet to evaporate water in a sample. By weighing before and after drying, the percentage of dry material can be measured. To get the amount of organic solids, the dried sample is then put into a muffle furnace where all the organic material is burned up. Again by comparing the weight before and after, the amount of organic solids can be deduced. However, this method has two main disadvantages: (i) the process is very time consuming, as the drying and burning take more than 24 hours for one sample, and; (ii) the energy consumption during these processes is enormous.

New online-measurement probes can be used to measure these parameters directly in the process instead of taking samples. For total solids, there are already systems available for field use. For example, Fig. 6 shows an ultrasound measurement unit that is increasingly being used in modern biogas plants. This can measure the amount of solids in a substrate as it is pumped through the feed line.

The online measurement of organic solids is more complicated. One promising method in this context is the use of NIRS (near infra-red spectroscopy, Fig. 7). The measurement equipment basically consists of a NIR-light source and a detector. The light source generates pulses of NIR-light which are used to illuminate the sample material. The detector then measures the reflected light spectrum (800–1600 nm) and compares it to the source spectrum.

In this way the concentration of various substances can be indirectly measured as different substances absorb light at different wavelengths. The downside is, that the system has to be calibrated specifically for every single substance that has to be measured, an exercise that must be repeated regularly as values drift significantly over time. NIR-spectroscopy also allows the measurement of other useful properties such as pH-Value as well as concentrations of organic acids like acetic acid and propionate acid. Nevertheless, this wide range of application at biogas plants has its price. One NIR-probe costs between 30 and 40 thousand Euro, depending on the configuration.

Figure 6 Ultrasound TS Probe by hf-sensor [16].

Figure 7 NIR-measurement system [17].

Figure 8 UV/vis-spectroscopy probe.

A similar approach to NIR-spectroscopy is UV/vis spectroscopy, which measures the absorption of ultraviolet light (200–750 nm) to determine the concentration of a certain substance in a liquid sample.

The technology comes from the wastewater treatment sector where it has been successfully used for several years. The main problem for the application on biogas plants is the high concentration of the different substances in the substrate and also the relatively high concentration of solids. In a pilot project researchers at the Cologne University of Applied Sciences have developed an automated sample preparation and dilution system that addresses these issues and installed it on an industrial biogas plant. Initial results are very promising [18].

These new technologies and their possible applications make it obvious, that the basis for the development of new control and optimization strategies is growing. Online process monitoring at biogas plants is possible and becoming more and more affordable.

5 Simulation Model

Biogas plant simulation models are valuable as tools for learning about and understanding the complex behaviour of anaerobic digestion processes and also as platforms for developing and testing new optimization and control strategies. To be of value for the latter, models have to adequately capture the different fermentation phases and inhibition factors as well as the fermentation process dependencies on internal and external influences that are responsible for non-linear plant behaviour. The ADM1 model, developed by the IWA (International Water Association) for anaerobic digestion, offers these features through its detailed representation of the various biochemical mechanisms involved.

In a recent work a biogas plant simulation was developed in Matlab using the ADM1 model implementation that comes with the Simba® toolbox. Simba®

is a Matlab software package for dynamic simulation of biological wastewater systems [19]. The simulation was designed to replicate the behaviour of a reference agricultural biogas plant near Frankfurt (Germany). The substrate feed of the reference plant consists of Cob Corn Mix (CCM), Rye and pig manure. Using basic online-measurements, the simulation model was calibrated to match biogas production and quality for different substrate combinations.

The complete simulation model implemented in Matlab consists of five elements: (1) substrate feed; (2) fermentation tank (ADM1 model); (3) final storage tank; (4) energy balance; (5) biogas analyses. All simulations were performed under the following conditions for the anaerobic digestion process:

- Fermentation occurs under mesophilic conditions (40 °C)
- The fermentation tank is ideally stirred
- The fermentation tank has a liquid phase of 1000 m^3 and a gas phase of 350 m^3

The calibrated simulation model allows the prediction of methane production as a function of the substrate feed composition. Figure 9 shows a model prediction in which the substrate feed can be increased up to a certain level until methane production collapses. Different substrates will increase or even decrease methane production, depending on their ingredients. The simulated methane production levels plotted in Fig. 9 match the behaviour of the full-scale reference biogas plant.

The breakdown of methane production can be attributed to many factors but the most common are:

- Critical concentration of organic acids
- High ammonia concentration
- High hydrogen sulfide concentration
- Critical concentration of heavy metals

Critical process states caused by acid and ammonia inhibition are captured by the simulation model, whereas inhibition resulting from sulfate reduction, the development of hydrosulfide and critical concentrations of heavy metals cannot be simulated. This is a limitation of the ADM1 model implementation employed. However, if needed, ADM1 can be expanded to include sulfate reduction as proposed by Fedorovich and Kalyuzhnyi in 2003 [20], but this has not been used for optimization purposes to date.

The availability of a validated simulation model allows powerful Computational Intelligence (CI) methods such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) to be used to estimate optimum operating parameters for the biogas plant. The application of these powerful population based optimisation procedures is only feasible with a simulation model because testing many different operating parameters at full-scale biogas plants is difficult and often not practical. For example, varying substrate feed parameters can affect process stability and cause extreme situations that are difficult to recover from.

Section 6 provides a brief overview of GAs and PSO and demonstrates the potential of this approach for the problem of estimating the optimum substrate feed combination for a biogas plant.

6 Optimization Using PSO and GAs

The optimization of the substrate feed with regard to its flow rate (throughput) and composition is a highly non-linear and complex optimization problem which cannot easily be tackled using conventional optimisation techniques. CI methods such as Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO), however, are perfectly suited to this task. GAs and PSO are both methods, designed to search among a collection of possible solutions for a designated solution. The most distinguishing characteristic of these CI methods, compared to analytic optimization methods, is that they have been developed to emulate natural highly non-linear phenomenons. In this case of GAs the inspiring natural example is genetic evolution while in the case of PSO it is the emergent complex patterns observed in the collective

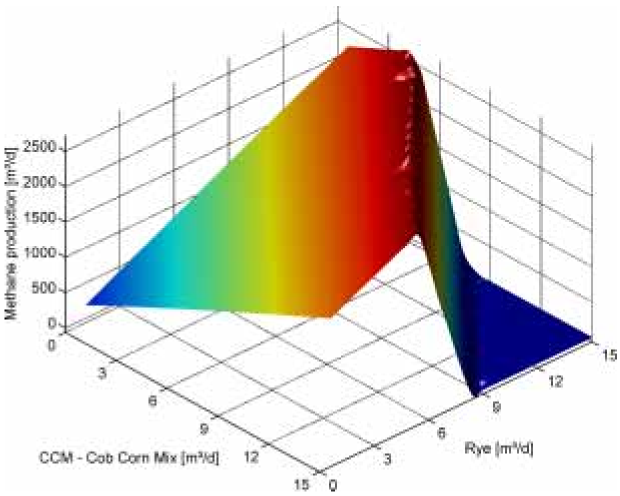

Figure 9 Simulated methane production for varying substrate feeds.

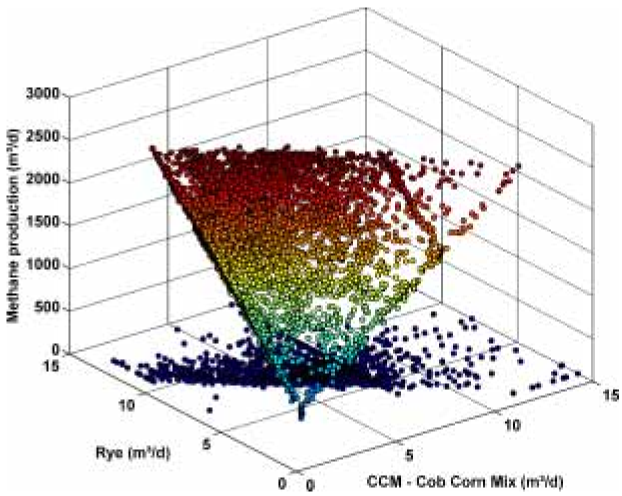

Figure 10 Methane production solution points generated by PSO.

movement of many species (e.g. bird flocking, animal herding and fish schooling).

A major strength of these methods is their global search capability. This allows a large search space to be explored and can lead to novel solutions that would normally not be considered. The global search capability of GAs and PSO in seeking a good solution to a complex problem is illustrated in Fig. 10. This shows the methane production resulting from various solutions generated by the PSO during 400 generations and highlights that both very low and very high substrate feeds are evaluated in an extremely non-linear state space. [21]

6.1 Introduction to Genetic Algorithms

GAs are described using biological terminology which differentiates them from other evolutionary computation methods. The most important terms are as follows:

- *Chromosome:* A representation of a possible solution to an optimization problem where parameter values are encoded using either binary, real-valued or tree encoding.
- *Genes:* Groups of bits or real values which encode one particular element of a possible solution (chromosome).
- *Crossover*: An operation in which genetic material is exchanged between two different chromosomes (parents) to generate new chromosomes (children).
- *Mutation*: An operation which randomly changes parts of a gene in a chromosome at randomly chosen places.
- *Population*: The set of chromosomes used to explore the optimization space. This can either be fixed or vary as optimization progresses.
- *Generation*: One optimization cycle of a GA.

As described in Mitchell [22] a basic genetic algorithm works as follows:

1. Generate a random initial population of n chromosomes.
2. Calculate the fitness $f(c)$ of each chromosome c in the population.
3. The following steps are repeated to obtain a new population with n offspring:
   a) Select two parent chromosomes based on the calculated fitnesses.
   b) Crossover the parents at a chosen point with a crossover probability p_c and create two offspring.
   c) Mutate the offspring at every position with mutation probability p_m and add the mutated chromosomes to the new population.
4. Exchange the current population with the newly generated population.
5. Repeat from step 2.

A single iteration of these steps represents one generation of the GA.

The most critical parameter in a GA is the fitness function which is used to evaluate potential solutions. If the fitness function is poorly chosen optimization results will also be poor. Finding the appropriate fitness function for a complex optimization problem is often the most difficult task. Furthermore, algorithm performance is sensitive to the choice of generation and population size, crossover and mutation functions and chromosome encoding; hence these parameters must also be carefully chosen for optimum results.

Table 2 Parameters for the GA.

GA parameters	Value
Number of generations	200
Population size	60
Probability of crossover	0.7
Crossover strategy	Intermediate
Mutation strategy	Adaptive feasible
Selection strategy	Elitism + Stochastic uniform

Genetic Algorithm Design

Design parameters such as population, number of generations, crossover function and mutation rate require careful selection in order to obtain good optimization results. Table 2 shows the parameters used in the GA for substrate optimisation. The GA has been created using the standard Matlab GA toolbox [23].

The crossover strategy *Intermediate* creates children as a weighted average of the parent solutions according to the following equations,

$$C_1 = P_1 + r\,(P_2 - P_1)$$
$$C_2 = P_2 + r\,(P_1 - P_2) \qquad (1)$$

where C_1 and C_2 are children of parent solutions P_1 and P_2, r is a uniform random crossover factor in the range [0, 1]. The mutation strategy *adaptive feasible* randomly generates mutations which are adapted based on previous successful and unsuccessful generations in order to remain feasible.

6.2 Introduction to Particle Swarm Optimization

PSO is a population-based evolutionary computation algorithm for problem solving which simulates social behaviour in swarms. In determining how to move, individuals in a swarm (particles) exchange information with their neighbours, thereby influencing their behaviour and eventually the movement of the whole swarm. This process allows a swarm to move towards the most interesting site in a search space, as information about interesting sites is slowly propagated to the whole swarm. Thus, in PSO, the behaviour of each particle in a swarm is governed by two basic principles: *particle communication* and *particle movement*.

Particle communication is controlled by the parameter K_N, defined as the number of neighbouring particles a particle is exchanging information with. To guarantee sufficient particle communication K_N has to be carefully selected. If it is too small the propagation of important information to all particles might take too long and if too large, particles might get stuck in a local optimum. The probability $P_r(t)$ for a particle to be reached at least once after the t^{th} run is described by the following formula [24], where N is the number of particles and K_N is the number of neighbours for information exchange.

$$P_r(t) = 1 - \left(1 - \frac{1}{N}\right)^{K_N^t} \qquad (2)$$

As the probability increases quickly with t, even with a small number of neighbours, K_N, information propagation throughout the whole swarm can be rapid.

The movement of a PSO particle in a search space is defined in terms of its position vector $\mathbf{x}(t)$ and three parameter vectors:

- *Velocity* ($\mathbf{v}$): The speed at which the particle moves through the search space.
- *Personal best position* ($\mathbf{p}$): The best position a particle has currently found.
- *Global best position* ($\mathbf{g}$): The best position found by informants of a particle.

Using these parameters a particle's position and velocity are updated at the t^{th} iteration as follows:

$$\begin{aligned} \mathbf{v}(t+1) &= c_1\mathbf{v}(t) + c_2(\mathbf{p}(t) - \mathbf{x}(t)) + c_3(\mathbf{g}(t) - \mathbf{x}(t)) \\ \mathbf{x}(t+1) &= \mathbf{x}(t) + \mathbf{v}(t) \end{aligned} \qquad (3)$$

Weights c_1 to c_3 are constants that determine the importance of the different vectors:

- c_1 represents the confidence of a particle in its direction of movement.
- c_2 and c_3 represent the confidence of a particle in its personal best position and its best reported global position, respectively.

Using these mechanisms a swarm of particles moves through a search space looking for an optimal solution to a defined optimization problem. In a similar fashion to GAs, at each iteration all particles are evaluated using a fitness function and this information is used to update the current position, personal best position and global best position of each particle.

Particle Swarm Optimization Design

PSO was implemented using a free Matlab toolbox developed by Birge [25] with algorithm parameters set as shown in Table 3. The values for personal and global best influence represent how much confidence a particle has in its personal best position and in the best position it has ever heard of, while the initial and final inertia weights reflect how much confidence a particle has in its own current position.

Table 3 Parameters for the PSO.

PSO parameters	Value
Number of runs	400
Number of particles	30
Personal best influence	2
Global best influence	2
Initial inertia weight	0.9
Final inertia weight	0.6

6.3 Fitness Function

The main challenge using GAs and PSO is to properly evaluate generated solutions and to rank them. This evaluation is done by a so called fitness function. As the fitness of a generated solution decides whether it will be considered or deleted, fitness function design is crucial to successful optimization. For some processes the fitness function is obvious, but for anaerobic digestion processes more than one parameter is important for the evaluation of possible substrate feeds. The key performance parameters of the fitness function are how far a substrate has been digested (D_s), energy consumption for pumps and heating of a fermentation tank (E), gas quality (G_q) and quantity (G_a), digester load (L_d) and penalties for exceeding pH (P_{pH}), substrate (P_s), or total solids (P_{TS}) limits. A weighted sum of these parameters, where each is scaled and multiplied with constant factors c_1 to c_8, constitutes the fitness function f considered here. The optimization objective is to minimize the fitness function.

$$f = \begin{cases} c_1D_s + c_2E + c_3G_q + c_4G_a + \\ c_5L_d + c_6P_{pH} + c_7P_s + c_8P_{TS} \end{cases} \qquad (4)$$

The weights for parameters G_a and L_d are selected to be greater than the others, because the first priority of substrate feed optimization is to tap the full potential of a biogas plant by maximizing biogas production and digester load in order to obtain maximum plant profitability. Therewith, other parameters like Energy consumption are of secondary importance.

6.4 Results and Discussion

Optimizing the substrate feed of biogas plants is the best way to directly influence biogas production and to react adequately to changing process states. This is achieved by varying the quantity and composition of the different substrates used for anaerobic digestion. In the case study considered here the substrate feed to be optimised consists of three substrates, Cob Corn Mix (CCM), Rye and pig manure.

To allow direct comparison between GAs and PSO the same fitness function is employed with both optimization strategies, In addition, both methods were executed for the same total number of simulation runs (12 000).

Figure 11 provides a comparison between the manually determined standard substrate feed and the optimised substrate feed determined by both GAs and PSO. The objective was to minimize the fitness function which resulted in a minimum substrate feed. The bar chart shows

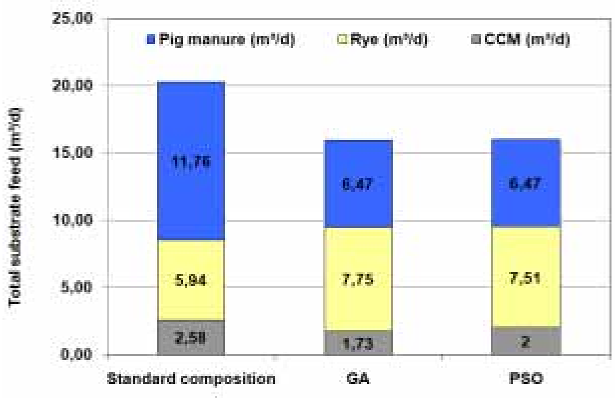

Figure 11 Comparison of standard and optimized substrate feed for an energy production of 300 kW.

the composition of substrate in each case and the quantity of substrate needed to achieve a power output of 300 kW.

The results show that there is great potential for improving biogas plant operation if the substrate feed is optimized. Figure 11 shows that the overall substrate feed can be reduced by 21% while achieving the same energy production, no matter, which optimization strategy is used. Furthermore, energy consumption for heating the fermentation tank and pumping substrate is reduced whereas the retention time of the substrate in the fermentation tank is prolonged, resulting in better substrate degradation.

While the final results of the optimization strategies are very similar, it is important to consider other factors, namely the computation time and the inter-run variability in results arising from the stochastic nature of the methods. The fact that many simulations have to be performed and their outcomes evaluated makes computation time one of the critical factors for the application

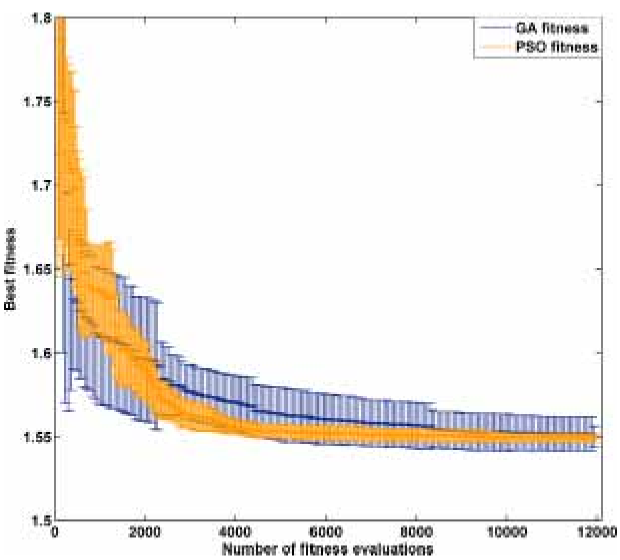

Figure 12 Improvement in the best fitness as a function of the number of fitness function evaluations for (a) GAs; and (b) PSO (average and standard deviations shown are based on 10 optimization runs).

of these methods. To evaluate the variability in results and the performance versus computation time trade-off the evolutions of the GA and PSO fitness function over 10 optimization runs was analysed and their average and standard deviations plotted in Fig. 12.

As can be seen GA and PSO achieve comparable results with the average final fitness of the PSO composition marginally superior to the GA (1.549 compared to 1.550). In addition, the variability of results obtained with PSO is much less than obtained with GAs (40%), hence PSO has a much greater likelihood of generating good optimization results in a given run.

When comparing the computational performance of PSO and GAs it has to be considered that each method requires a different number of fitness function evaluations per generation and takes a different number of generations to converge. For example the best GA result required 196 generations with 60 simulations for each generation to reach the best fitness, whereas the best PSO run needed 337 iterations with 30 simulations each. This resulted in a total of 11 760 biogas-plant simulations for the GA and 10110 simulations for PSO, which clearly highlights that PSO is approximately 14% faster than the GA in this instance. Compared to the gain in final fitness this saving in simulations is more important (each simulation takes approximately 10 seconds on a 2.4 GHz Quad-Core Pentium Processor). Thus PSO is the preferred optimization strategy for this application. It further should be highlighted that both methods practically calculate the same result, although they are of probalisitic i. e. non-deterministic nature, and use totally different algorithms. This empirically proofs the reliability and stability of these methods, for which an analytical stability proof is not possible.

To sum up, the availability of a calibrated simulation model offers important advantages for biogas plant control and optimization. It allows the simulation and evaluation of hundreds of substrate combinations so that optimal feed parameters can be determined for specific situations under specified conditions. In addition, substrate feed optimization results can be evaluated against existing feed strategies with respect to important performance criteria such as biogas quantity, quality and pH-value, as well as substrate and energy costs. It also allows plant operators to classify the substrate mixes they currently use as well as predict, in advance, the consequences for biogas production of previously unseen operating conditions.

Optimization results show that an intelligent optimization strategy involving GA or PSO model-based optimization of substrate feed, can substantially improve the efficiency of biogas plants without compromising process stability. In particular, the reduction of substrate feed of 21% is very high, but this may differ from plant to plant as it very much depends on the optimization potential of individual biogas plants. The direct comparison of a GA and PSO applied to the same application revealed interesting results, showing that both methods reach similar fitness values, but computation time to reach an optimum is significantly different. PSO has proven to be more efficient than GAs with the result that similar results to GAs can be achieved a lot faster using PSO.

7 Conclusions

The current state of the biogas market shows a steadily growing need for new developments in the areas measurement, control and optimization. All these areas are still in their infancy, when it comes to full-scale applications and the necessary investment costs are very high. Changing market conditions means that improving plant efficiency is becoming more and more important to the long term viability of operating companies. Consequently there is increasing demand for biogas plant manufacturers to offer control and optimization systems that can deliver improved efficiency. This system approach relies on the availability of robust on online-measurement systems.

Furthermore, many biogas plants in Germany and all over Europe that have been running for a few years experience problems due to long-term effects such as sedimentation and the need to change substrates. The installation of appropriate online-measurement equipment and easy-to-handle optimization systems to address these problems presents an enormous market opportunity that has yet to be exploited.

These two developments offer great opportunities for the intelligent use of advanced automation systems in the future. The use of validated simulation models and CI-methods is merely the first step.

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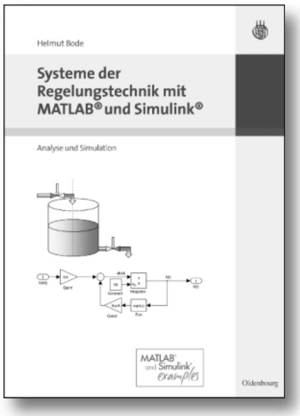

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