GA Optimization for Biogas Flow Rate in Novel Energy Biocell Landfill

Ahmad Qasaimeh, Maria Elektorowicz, and Iwona Jasiuk

Abstract**—**In landfills, biogas moves hysterically through the porous media in the least resistant pathways. In this research, new design approach of landfill is being examined for methane and carbon dioxide transfer through controllable hydrophobic permeable medium within available volume and dominant conditions. Hence, optimization for biogas volumes and mass transfer rates through the hydrophobic polymer is a key factor for design. Genetic algorithm is used here to design the micro-scale gas transfer within the hydrophobic polymer medium. Genetic algorithm is used to optimize a function that represents design solutions for daily biogas rates from which mass and volumes of biogas within the time of service are synchronized for the design of engineered hydrophobic landfill energy cells.

Keywords**—**Genetic Algorithm, optimization, biogas, transfer, landfill, energy, biocell

I. Introduction

THE The waste in municipal solid waste (MSW) landfill undergoes biochemical processes that produce methane and carbon dioxide (biogas).The biogas pressure and composition vary during the life of the landfill. The methane and carbon dioxide generation increases the pressure gradients leading to the gas advective flow. The concentration gradients lead to the gas diffusion. Diffusion is a generic transport process, encountered in fluids, by which molecules that can move randomly are redistributed until equilibrium is reached when concentration becomes uniform [10]. Temperature changes can also give rise to pressure differences and lead to gas migration [11]. Following the path of least resistance, gas will migrate either vertically to the atmosphere or laterally beyond landfill boundaries in surrounding geological formations. In the latter case, gas eventually reaches the atmosphere [12].

II. Biogas Transport in Hydrophobic Porous Polymer

When biogas moves through porous media like soil and rock strata, many factors affect the transport. The porosity and water content are vital factors affecting the biogas transport in porous media. It was concluded that increasing the porosity and decreasing the water content provide more efficient biogas transport (convection and diffusion). Consequently, the proposed medium in this research should respond to the following criteria:

- Negligible water content (more permeable)
- No microbial growth inside (no clogging)
- High porosity (more air filled voids)
- Light and easily reformed material
- Cheap and recyclable material

Subsequently, a hydrophobic porous polymer seems ideal medium for biogas containment. The hydrophobic medium can be a material such as polymers (e.g. polystyrene PS, polyethylene PE). To fulfill sustainable development principles, polymers used for hydrophobic medium can also be formed from recyclable materials available in the landfill dump. Another source of sustainable materials for polymer formation is wasted polymers during wrong polymerization processes take place occasionally in the factory. Referring to the objective of the research, biogas capture and control is the main issue. The experimental procedure entails tests that check the biogas relevant processes that affect its collection and control. Styrofoam material should be tested to check its permeability and functionality for conveying the biogas by diffusion and convection transport. Therefore, series of tests have been conducted to determine the coefficients of permeability, diffusion, and conductivity for Styrofoam hydrophobic medium. Collected information about parameters (temperature variation, pressure gradient, and concentration gradient) were generated to obtain their effect on polymer-gas conductivity coefficient, gas convection rates, gas diffusion coefficient, and gas diffusion flux through the porous Styrofoam polymer medium. Figure 1 shows the effect of temperature variation on the coefficients of conductivity and diffusion for methane and carbon dioxide in the porous hydrophobic polymer medium [9].

In the landfill, the important parameters (temperature, pressure, and biogas concentration) are variable. Therefore, biogas behavior is stochastic in addition to the variation of gas ratio in the emission. The experimental data in Figure 2 shows the biogas flux vs. different pressure gradients where each curve satisfies certain biogas ratio, simulating a situation on landfill, particularly at different ages of the landfill [9].

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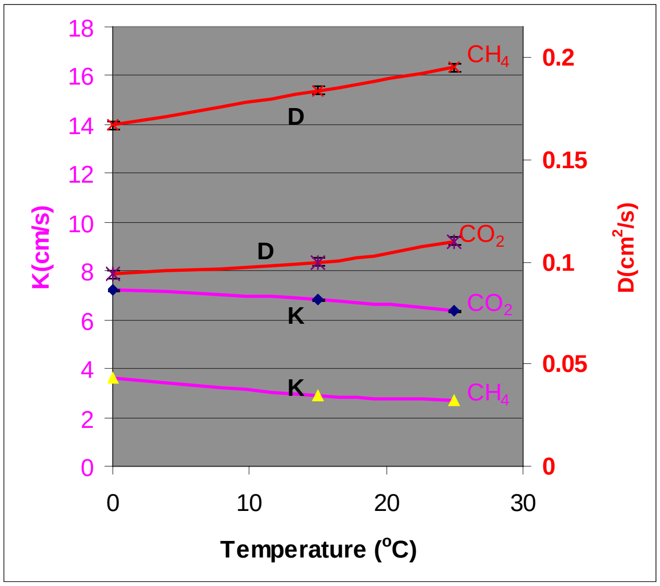

Figure 1. Effect of Temperature Variation on Coefficient of Conductivity (K) and Coefficient of Diffusion (D) (at atmospheric pressure) for Biogas in Hydrophobic Medium [9].

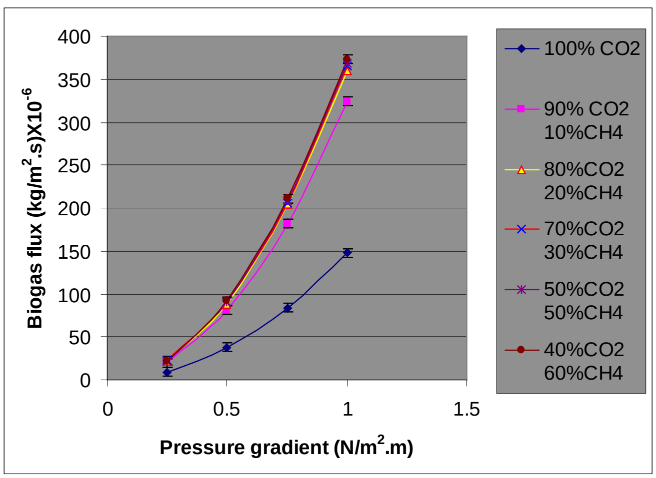

Fig. 2: Biogas flux for different biogas percentages [9].

III. GA DESIGN

Genetic algorithms (GA) deal with stochastic search method introduced in the 1970s by researchers such as Holland (1975) and Ingo Rechenberg (1973) [6, 7]. GA is an optimization technique that simulates and imitates the analogy of biological genetics and emulates the phenomenon of selection of the fittest approach [2]. A GA is generally characterized by:

- Coding scheme for each possible solution, using a finite string of bits (called chromosome).
- Fitness value that provides the quality of each solution.
- Initial set of solutions to the problem, called initial population, randomly generated or chosen according to prior knowledge.
- A set of reproduction, mutation and natural selection operators that allows the development of the population [1, 5, 8].

Based on generalization of natural evolutionary processes, genetic algorithms operate on a population of solutions rather than a single solution. Each individual of a population is a potential knowledge base that is encoded before applying four operations: crossover, mutation, evaluation and natural selection, and decoding [8].

Genetic algorithms duly solve natural and ambiguous real world problems. One example of genetic algorithm applications is in environmental engineering. Using genetic algorithms in combination with fuzzy logic systems for instance should conquer vagueness in natural environments. One example of GA-Fuzzy applications in environmental engineering conducted in Concordia University is the fuzzy decision support system that uses genetically generated knowledge base to evaluate the capability of constructed wetland sediments to adsorb mercury [4, 3].

Genetic algorithm is being used here to optimize the design of micro-scale of biogas transfer in the permeable hydrophobic polymer medium in landfill biocells. The genetic algorithm proceeds in iterative processes to achieve the optimized solution that is being represented by transfer function that represents the simulation of biogas flux due to input values of biogas percentages during the landfill time. The solutions are evaluated and optimized until steady state is achieved till the genotypes in the population are very similar if not identical to each other.

The progression of the population is achieved by reproduction of the best individuals based on their ability to endure natural selection. Reproduction is mainly carried out by crossover or mutation. Crossover exchanges bits of genotype of two parents to produce the genotype of two children. Mutation is a random inversion of a bit in the genotype of a new member of the population. Mutation allows trying completely different solutions. The capacity of each individual to endure natural selection is evaluated by objective function. The objective function evaluates the capacity of the knowledge base to approximate the sampled data. This fitness value can be computed as the root mean square error method:

$$RMSE(\hat{\theta}) = \sqrt{E(\hat{\theta} - \theta)^2} \qquad (1)$$

Natural selection is performed on a population by keeping the most promising individuals based on their fitness. This is equivalent to using solutions that are the closest to the optimum. For phenotype ω that is drawn from some set of ψ, fitness optimization is the optimal value of function as $f(\omega)$ that shows how successful the phenotype is:

$$\min \ f(\omega) \quad : \quad \omega \in \psi \qquad (2)$$

When genetic algorithm is in a steady state, a newly-born child replaces the worst genotype of the population in the process of creating solution using genetic operators. This process, as shown in Fig.3 is repeated until optimization criterion is met, which normally takes place when many of iterations have been accomplished.

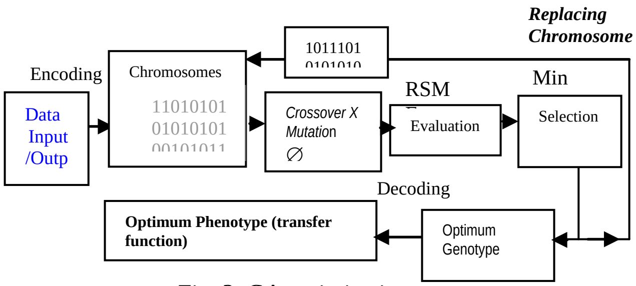

Fig. 3: GA optimization processes

The optimization of solutions via iterative generations as shown in Fig. 4 drives towards the best phenotype that is represented by the following transfer function:

$$F5 = (z+0.888)/ (z-0.704) \qquad (3)$$

Solution F5 is the most optimal solution and therefore it is used as a representative transfer function for simulation of the biogas transport through the permeable hydrophobic medium. The transfer function is used in Simulink for the design of biogas volume and mass. As shown in Fig. 5, the output of the transfer function is scaled to the in-situ case condition by function

$$f(u) = 0.06 \times u \qquad (4)$$

The daily mass transfer rate (dm/dt) shown in Fig. 6, is used to find the total biogas mass and volume. Fig. 7 shows biogas design volumes and percentages in constructed landfill biocells during 40 years.

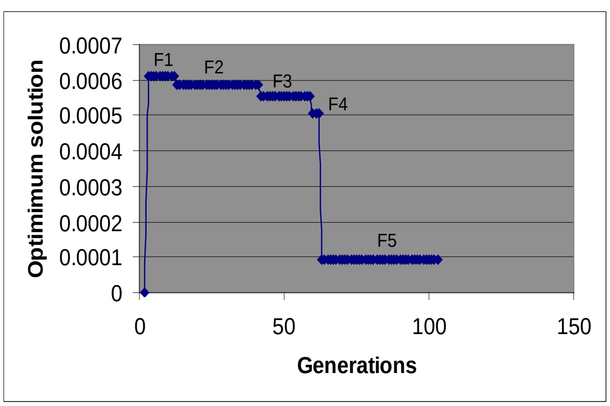

Fig. 4: Optimum solutions via iterative generations

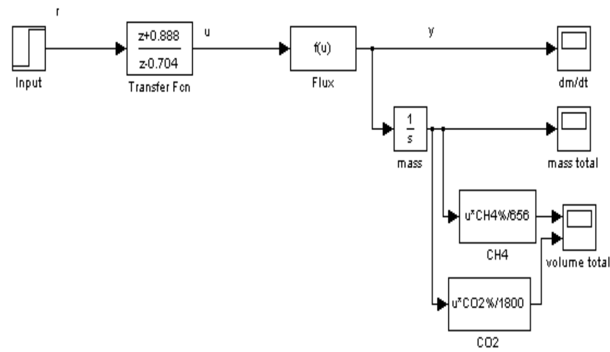

Fig. 5: Simulink scheme for finding daily biogas mass transfer rate, mass, and volume using optimum transfer function

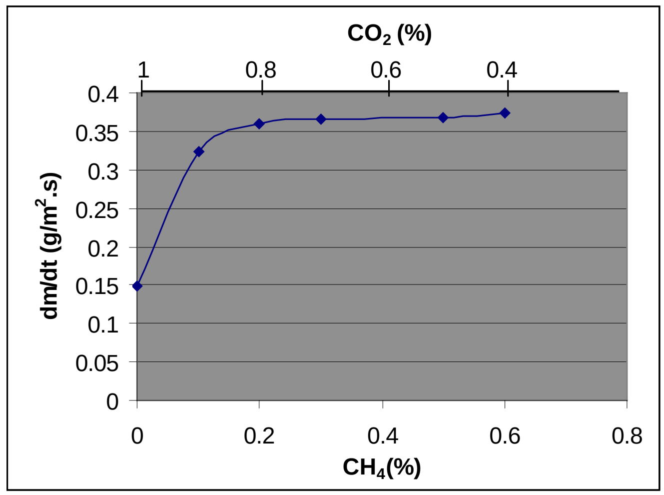

Fig. 6: Biogas Mass Transfer Rate (dm/dt) vs. Different Biogas Percentages at Pressure Gradient 1 $N/m^2.m$ (within 40 years and average temperature 25 ^oC)

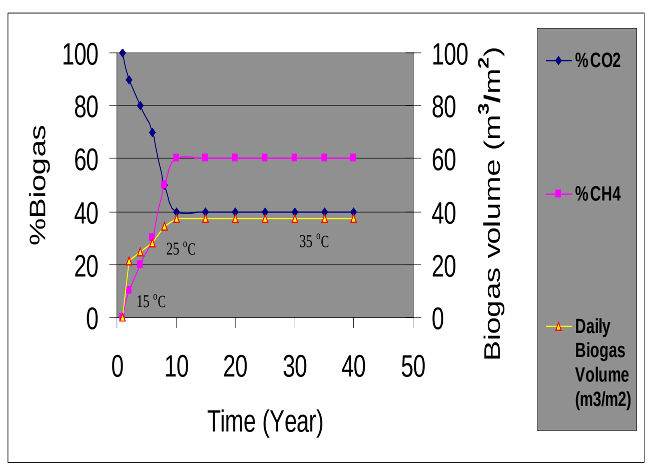

Fig. 7: Biogas design volumes in landfill during 40 years age

This GA approach designs volumes and percentages for biogas mixture (CH_4, CO_2) in biocell landfill during 40 years. The capacity and the properties of hydrophobic porous polymer used in biocell landfill should withstand the biogas mixture volumes and mass transfer requirements.

IV. CONCLUSION

Genetic algorithm is used to optimize a transfer function that represents solutions for daily biogas transfer rates; from which, mass and volume of biogas within the time of service are used for design of the hydrophobic permeable polymer that transfers and conveys the biogas in constructed landfill biocells.

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