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Research Article

NATURE INSPIRED TECHNIQUES TO SOLVE COMPLEX ENGINEERING PROBLEMS

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ABSTRACT

Presence of heavy metals and toxic chemicals in effluent waste water, which usually discarded to local water bodies, pollute the land, air and water. These pollutants effect the environment and human beings. Due to stringent environmental regulations, researchers are exploring the best way to treat the effluent before they are discarded. Biofilm process are observed to be all the more expanding on the grounds that they are ecological benevolent and less vitality serious. The use of biofilm reactor models to genuine useful issues endures because of the absence of learning of exact dynamic models and instability in the model parameters. Effective demonstrating of bioreactors, along these lines, requires choosing a suitable active model and precise assurance of its parameters. Converse estimation of model parameters by means of numerical displaying course is known as backwards demonstrating (IM), which is an alluring contrasting option to the trial techniques. In this approach, the parameters are resolved as an outcome of the approval of the procedure demonstrate with the guide of measured information. Parameter estimation by IM includes minimization of a target capacity and therefore needs the support of productive improvement calculations. In this review, a novel streamlining strategy is proposed in view of insect state improvement (ACO) meant as ACO-IM and connected for the assurance of dynamic and film thickness parameters of biofilm models of a trial settled bed anaerobic reactor utilized as a part of the treatment of industry waste water. The aftereffects of this review are assessed as for scientific models, active and film thickness expressions.

INTRODUCTION

Water Effluent waste water from various industrial sources are polluting the land, water and air. Presence of heavy metals and toxic chemicals in aqueous environment will cause severe pollution to aquatic organisms, flora and fauna besides threatening to human health. It was observed that intake of these polluted water primary causes cancer and other long term medical effects. These heavy metals cannot degrade biologically and presence of this heavy metals in environment pollute air, water and soil and was reported to cause anorexia, cerebral pain, and other mental disorders. Due to these lethal and long term effects, stringent environmental regulations are implemented to treat the effluent waste water before it is disposed to local water bodies. Biofilm procedures are progressively utilized for waste water cleaning as they are natural cordial and less vitality escalated. Biofilms are agglomerations of microorganisms or microbes, which because of their

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metabolic movement change over the contaminant parts of the waste waters into safe items. The conduct of a biofilm is dictated by an assortment of organic, substance and physical procedures interior to the film and additionally communications between the biofilm and its condition. The brilliant biomass maintenance with sensible water driven confinement times of biofilm procedures make them alluring when bacterial development rates are moderate or when the mixes are inhibitory or gradually debased. A wide range of sorts of reactors have been created throughout the years, which incorporate settled film reactors, streaming channels, pivoting organic contactors, submerged bio channels and fluidized bed reactors. Fixed bed biofilm reactors are dynamically used for anaerobic treatment of waste waters. The guideline good position of the fixed bed techniques is that high volumetric densities of microorganisms can be gathered by basic association as biofilms. The high thickness of biomass accumulation permits astounding treatment performance in genuinely smaller reactor volumes, which is financially advantageous. Since the biofilm and its condition outline a bewildering structure, it is frequently difficult to explore the biofilm reactors characteristics. Mathematical models could be very useful in examining such scenarios.

The utilization of biofilm reactor models to genuine useful issues endures because of the absence of learning of exact active models and vulnerability in the model parameters. Effective demonstrating of bioreactors in this manner requires choosing an appropriate kinetic model and precise determination of its parameters. A few endeavors have been made in the past to estimate the parameters of kinetic models of biofilm reactors (Radu, *et al*., 2010; Nguyen and Shieh, 1995; Karri, *et al*., 2017; Manenti, *et al*., 2013). Numerical assessment of the active parameters for biofilm procedures is an appealing contrasting option to the test strategy as revealed by different specialists (Sarti, *et al*., 2004; Khorasheh, *et al*., 2002; Rao, *et al*., 2009; Spigno, *et al*., 2004; Karri and Babovic, 2016; Abusahmin, *et al*., 2017; Karri, 2011). By this approach the parameters are resolved as an outcome of the approval of the biofilm demonstrate with the assistance of measured information. This approach is otherwise called opposite demonstrating in which the model parameters are resolved with the end goal that the conduct of the procedure show approximates the watched procedure conduct. In this way a thorough scientific model that satisfactorily portrays the procedure should be utilized as a part of request to get exact estimation of parameters and to guarantee solid model forecasts. As of late, hybrid evolutionary optimization methods are being utilized in place of conventional methods to solve variety of optimization problems (Rao, *et al*., 2010; Venkateswarlu and Reddy, 2008; Roubos, *et al*., 1999). There is a need to develop the biofilm reactor model that ought to perform in real circumstances with changing organic loading rates and encourage stream rates with various water driven maintenance times. The improvement of such a model requires practical information comparing to various working states of biofilm reactor. The development of such a model requires realistic data corresponding to different operating conditions of biofilm reactor.

This work presents scientific and motor demonstrating parts of settled bed anaerobic biofilm reactor, wherein microorganisms append themselves onto a strong surface, restricting together in grid sludge like matter to shape a biofilm. A numerical approach in light of backwards displaying (IM) is utilized to gauge the dynamic and film thickness parameters as a result of the approval of the procedure show with the guide of measured information. Since converse displaying includes the minimization of a goal work, productive advancement techniques are expected to appraise the parameters in biofilm models. In this review, a novel improvement technique is proposed for parameter estimation in light of a subterranean insect framework which copies the way that ants are equipped for finding the most limited way from a nourishment source to their home by saving a trial of pheromone amid their walk. This exploration work adjusts insect settlement streamlining (ACO) to build up a novel approach called ACO-IM, which has been connected for the backwards estimation of active and film thickness parameters of biofilm models of a trial settled bed anaerobic reactor. Consequences of this review are assessed regarding the thoroughness of numerical models, film thickness and kinetic models, and optimization algorithms.

MATERIALS AND METHODS

Characteristics of effluent waste water

Initially, experiments are conducted for wastewater treatment of industrial distillery in an anaerobic biofilm reactor as shown in (Fig. 1). The characteristics of industrial distillery wastewater is given in Table 1. Thirteen experiments are conducted with gravel stones as the packing for growth of biofilm, and the hydraulic retention time varied from 2 - 12 days for each feed conditions. The experiment after each hydraulic retention time is continued for 13 days by which the operation approaches steady state condition. The variation of COD, BOD and pH

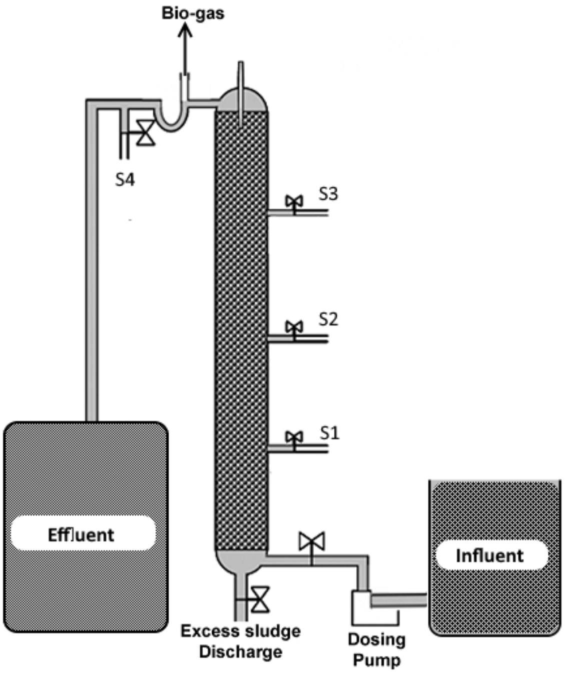


Fig. 1 Experimental setup for treatment of industrial distillery water-water.

Table 1. Distillery wastewater characteristics

Property	Value
Chlorides	0.18 kg/m^3
Phosphates	0.125 kg/m^3
Sulphates	3.7 kg/m^3
Nitrates	0.7 kg/m^3
pH	6.9
BOD	38.9 kg/m^3
COD	67.46 kg/m^3
BOD/COD	0.577
Total solids	3.49 kg/m^3
Total suspended solids	0.59 kg/m^3
Total dissolved solids	2.9 kg/m^3

with hydraulic retention time of 4 days and inlet concentration of 4950 mg/L is shown in Table 2. It is observed from this experiment that at sample ports S1 & S2 very lower removal, whereas as the fluids move higher, it results in higher removal efficiency.

Mathematical modelling

To estimate the dynamics and understand the inherent characteristics of a system, mathematical modelling is a good tool. In engineering systems to estimate the influence of driving parameters, number of experiments has to be carried. This process is not only expensive but also time taking. To mimic, the experimental process and study the sensitivity of process parameters, a robust mathematical model is must. In the effluent treatment of waste water, fixed bed biofilm reactors are extensively used. The utilization of biofilm reactor models to genuine viable issues endures because of the absence of learning of exact motor models and instability in the model parameters. Accordingly a thorough numerical model that satisfactorily depicts the procedure should be utilized as a part of request to acquire exact estimation of parameters and to guarantee dependable model expectations. Mathematical modelling varies with simple model to multi-dimensional model with varying complexities. These models are used to find their suitability while meeting the twin objectives of simplicity and rigor. The calculated biofilm process demonstrating the substrate move profile in a section of biofilm reactor in radial direction is shown in (Fig. 2).

Mathematical model

The substrate concentration is assumed to vary both in the axial and radial directions. The bulk fluid phase describing the physical diffusion in the biofilm is described as

$$u\frac{dc}{dz}=\frac{\varepsilon D}{r}\left[\frac{\partial}{\partial r}\left(r\frac{\partial c}{\partial r}\right)\right]-k_g a_v\left(c-c_s^s\right)$$

with boundary condition:

$$c = c_0 \text{ at } z = 0 \tag{1}$$

Here D is substrate diffusion coefficient in the bulk fluid.

The solid phase equation for the biofilm is given by

$$\frac{D_f}{\xi}\frac{d}{d\xi}\left(\xi\ \frac{dc_s}{d\xi}\right)-r_s\left(c_s\right)=0 \tag{2}$$

Where D_f is substrate diffusion coefficient in the bio-film.

Biofilm kinetics

The substrate consumption rate, r_s in a biofilm can be assumed to follow Monod kinetics which is expressed as

$$r_s=\left(\mu_{\max}\rho_s / Y\right)\frac{Cs}{K_s+C_s} \tag{3}$$

Biofilm thickness

The thickness of the biofilm (L_f) which has a significant influence on the substrate conversion is determined by the substrate flux into the biofilm from the bulk fluid. It was observed that the decay of biomass caused by shear stretch assume an essential part in deciding the rate of biofilm thickness and in this manner the general response rate. The biofilm thickness fundamentally relies on upon the substrate

Table 2. Variation of COD, BOD and pH of Industrial distillery wastewater with hydraulic retention time of 4 days and inlet concentration of 4950 mg/L

No of Days	COD (mg/L)				pH				BOD (mg/L)			
	S_1	S_2	S_3	S_4	S_1	S_2	S_3	S_4	S_1	S_2	S_3	S_4
1	2920	2640	2400	2140	6.85	7.3	7.76	8.43	1480	1280	980	890
2	2880	2520	2380	2040	6.85	7.32	7.88	8.44	1460	1260	940	880
3	2780	2480	2320	1960	6.85	7.41	7.97	8.25	1420	1220	920	890
4	2740	2460	2240	1880	6.75	7.32	7.88	8.35	1380	1160	940	890
5	2740	2460	2160	1820	6.94	7.41	7.97	8.44	1360	1080	920	880
6	2720	2320	2120	1760	6.94	7.22	7.97	8.35	1380	1040	900	860
7	2660	2240	2080	1680	6.85	7.32	7.88	8.25	1360	1060	920	860
8	2640	2160	1960	1620	6.85	7.41	7.79	8.35	1320	1040	900	870
9	2660	2080	1920	1580	6.94	7.32	7.69	8.35	1280	1020	880	820
10	2580	2060	1840	1580	6.85	7.13	7.69	8.25	1260	1020	860	790
11	2460	2040	1780	1550	6.85	7.32	7.79	8.25	1220	980	860	760
12	2360	2060	1760	1530	6.85	7.13	7.69	8.35	1180	980	820	740
13	2330	2030	1730	1530	6.94	7.32	7.69	8.35	1180	960	800	730

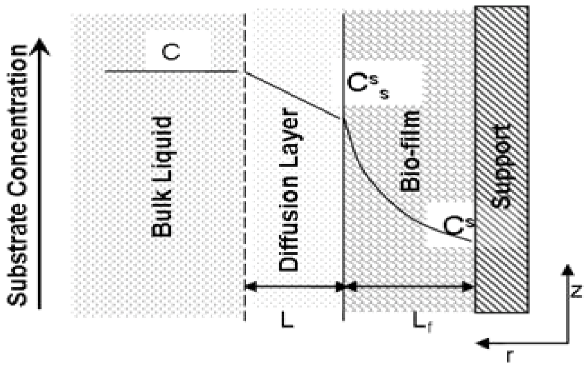


Fig. 2 Illustration of varyiation of substrate concentrate profile in biofilm model.

fixation in the mass fluid and the fluid water power. Subsequently, it is estimated that the biofilm is made out of a static segment and a varies with the hydraulic loading rate which is expressed as

$$L_f = a + b\ OLR \tag{4}$$

Where *a*, and *b* are film thickness constants to be estimated.

Numerical methods and optimization algorithms

The fluid phase Eq. (1) along with its boundary condition Eq. (2) is solved by Runge-Kutta 4th order method for the axial direction and for the radial direction it is solved by orthogonal collocation on finite elements. The objective of this research study is to set up a structure for the framework with concurrent assessment of kinetic and biofilm thickness parameters. An approach in view of inverse modeling (IM) is utilized to assess the parameters included the film thickness and kinetic expressions as a result of the scientific modeling procedure. These parameters are assessed by utilizing nonlinear global optimization strategy inspired from a heuristic subterranean insect based framework. The film thickness and kinetic parameters therefore assessed are utilized alongside the procedure conditions to fathom the numerical models keeping in mind the end goal to acquire the forecasts for substrate focuses. The model anticipated substrate focuses at the exit of the biofilm reactor are contrasted and the test esteems. A quadratic target capacity is characterized as a blunder capacity, which is limited through an iterative arrangement. The iterative meeting prompts the assurance of the film thickness and kinetic parameters.

Ant Colony Optimization for Inverse Modeling (ACO-IM)

A global search algorithm called ant colony optimization (ACO) is adapted in this work for the determination of the film thickness and kinetic parameters of fixed bed biofilm bioreactor. Through inverse modeling (IM) strategy, the parameters are estimated based on an objective function (J) as shown in Eq. (5), which defines the deviation between the actual values and corresponding process model predictions.

$$J = f(\alpha) = \sum_{i=1}^{l} (y_i - \hat{y}_i)^2 \tag{5}$$

Here $\propto$is the vector of parameters, $y_i$and $\hat{y}_i$ are the measured value and corresponding predicted value respectively for the i^{th} variable. ACO which is inspired by the foraging behavior of ants is introduced by (Dorigo and Caro, 1999) and is one of the most successful heuristic techniques to solve nonlinear problems. Thismethod mimics the way real ants find the shortest route between a food source and their nest as shown in (Fig. 3). Such searchingapproach is utilized in ACO algorithm to solve a number of optimization problems (Rao, *et al*., 2010; Dorigo and Caro, 1999; Dorigo, *et al*., 2000).

The framework of ACO-IM problem is described in in (Rao, *et al*., 2010), hence it is not presented herein detail. The possible number of pathways, N that the ants can travel through the parameter space $\propto$ are given by $N=M^{\propto}$. Each ant has to follow one of the pathways from the pathway-structure list shown on the left side of (Fig. 4). Accordingly, each ant will follow any one of the N pathways, e.g., pathway 3 (1,1, 3), or pathway 10 (3, 1, 1), as shown in (Fig. 4). This ACO mimic the strategy of performing the tasks such as selection of pathways, remembering the parameter range along the pathways, and updating the path based on the value of objective function.

Initially, the constants, Cc, A and C_S in ACO-IM strategy has to be evaluated first, before it is implemented for parameter optimization of film thickness and kinetic models in biofilm reactor,. In order to evaluate these constants, the ACO-IM is applied to six test functions. These test functions form as a benchmark, as their global minimum is already known, hence the above said constants can be tuned to achieve global minimum for each test function.

Test cases with varying degree/variables

To verify the efficacy of proposed ACO-IM, a set of six optimization functions with varying number of variables (parameters) was employed as follows and the global minima of these functions shown in (Fig. 5).

(a) **Quadratic (Booth) function**

$$f(x_1,x_2)=(x_1+2x_2-7)^2+(2x_1+x_2-5)^2$$

Number of variables: n = 2

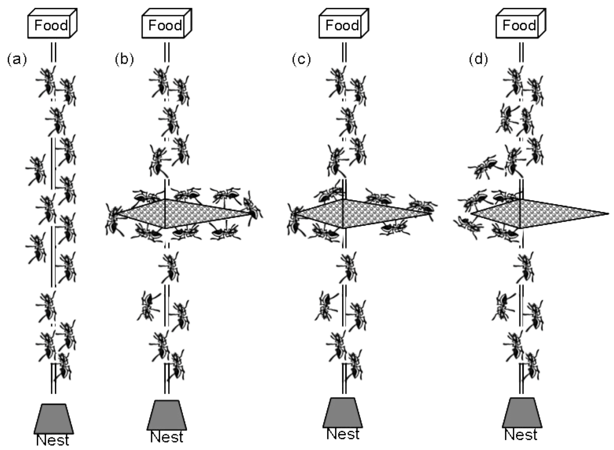


Fig. 3 Self adaptive behavior of find the shortest path between nest and food source.

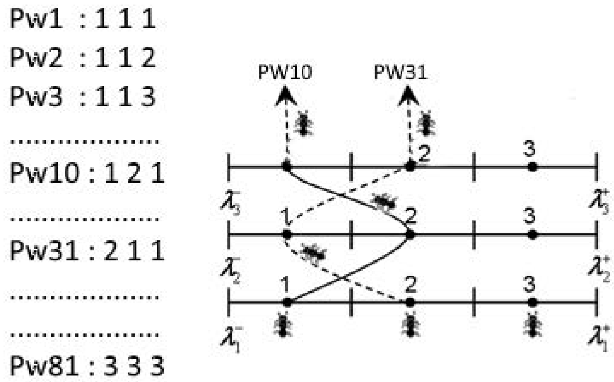


Fig. 4 Schematic representation of ACO strategy in selecting the pathways and evaluating the objective function for each path way.

Search domain: −10 ≤ xi ≤ 10, i = 1, 2.

Several local minima and global minima found with ACO-IM is x* = (1, 3), f(x*) = 0

(b) **Beale function**

$$f(x_1,x_2)=(x_1x_2-x_1+1.5)^2+(x_1x^2{}_2-x_1+2.25)^2+(x_1x^3{}_3-x_1+2.625)^2$$

Number of variables: n = 2.

Search domain: −4.5 ≤ x_i ≤ 4.5, i = 1, 2.

Global minima found with ACO-IM is: x* = (3, 0.5), f(x*) = 0.

(c) **Hump function**

$$f(x_1,x_2)=1.032+4x_1^2-2.1x_1^4+\frac{1}{3}x_1^6+x_1x_2-4x_2^2+4x_2^4$$

Number of variables: n = 2.

Search domain: -5 ≤ x_i ≤ 5, i = 1, 2.

no local minimum except the global ones.

Global minima: x* = (0.089, -0.712), (-0.089, 0.712),f(x*) = 0.

(d) **Powell quartic function**

$$f(x_1,x_2,x_3,x_4)=(x_1+10x_2)^2+5(x_3-x_4)^2+(x_2-2x_3)^4+10(x_1-x_4)^4$$

Number of variables: n = 4.

Search domain: −4 ≤ x_i ≤ 5, i = 1, 2… n. and global minima found with ACO-IM is x* = (3,-1, 0, 1), f (xi*) = 0

(e) **Rosenbrock function**

$$f(x)=\sum_{i=1}^{n-1}\left[100(x_i^2-x_{i+1})^2+(x_i-1)^2\right]$$

Number of variables: n

Search domain: −5 ≤ xi ≤ 10, i = 1, 2… n.

Several local minima is found and the global minima: x* = (1, 1…1), f (xi*) = 0

(f) **Brown Function**

$$f(x)=\sum_{i=1}^{n-1}\left[\left(x_i^2\right)^{x_{i+1}^2+1}+\left(x_{i+1}^2\right)^{x_i^2+1}\right]$$

Number of variables: n

Search domain: $-1 \le x_i \le 4$, i = 1, 2… n.

Several local minima is found and the global minima: x* = (0,0,…0), f (x_i^*) = 0

To obtain the global values of the above known functions, the constants C_c, A and C_S are perfectly tuned and the best values are found to be 0.5, 1.0 and 0.3 respectively.

Implemention of ACO-IM to estimate the film thickness and kinetic parameters

With the above fine-tuned parameters and confidence on the efficacy of ACO-IM, this optimization strategy is implemented for the determination of the film thickness and kinetic parameters of fixed bed biofilm bioreactor. Based on the objective function defined, the inverse modelling approach is adapted and found the best set of values for the parameters, $\mu_{\max}\rho_s/Y$, K_s, a and b are found to be 29.80, 0.102,

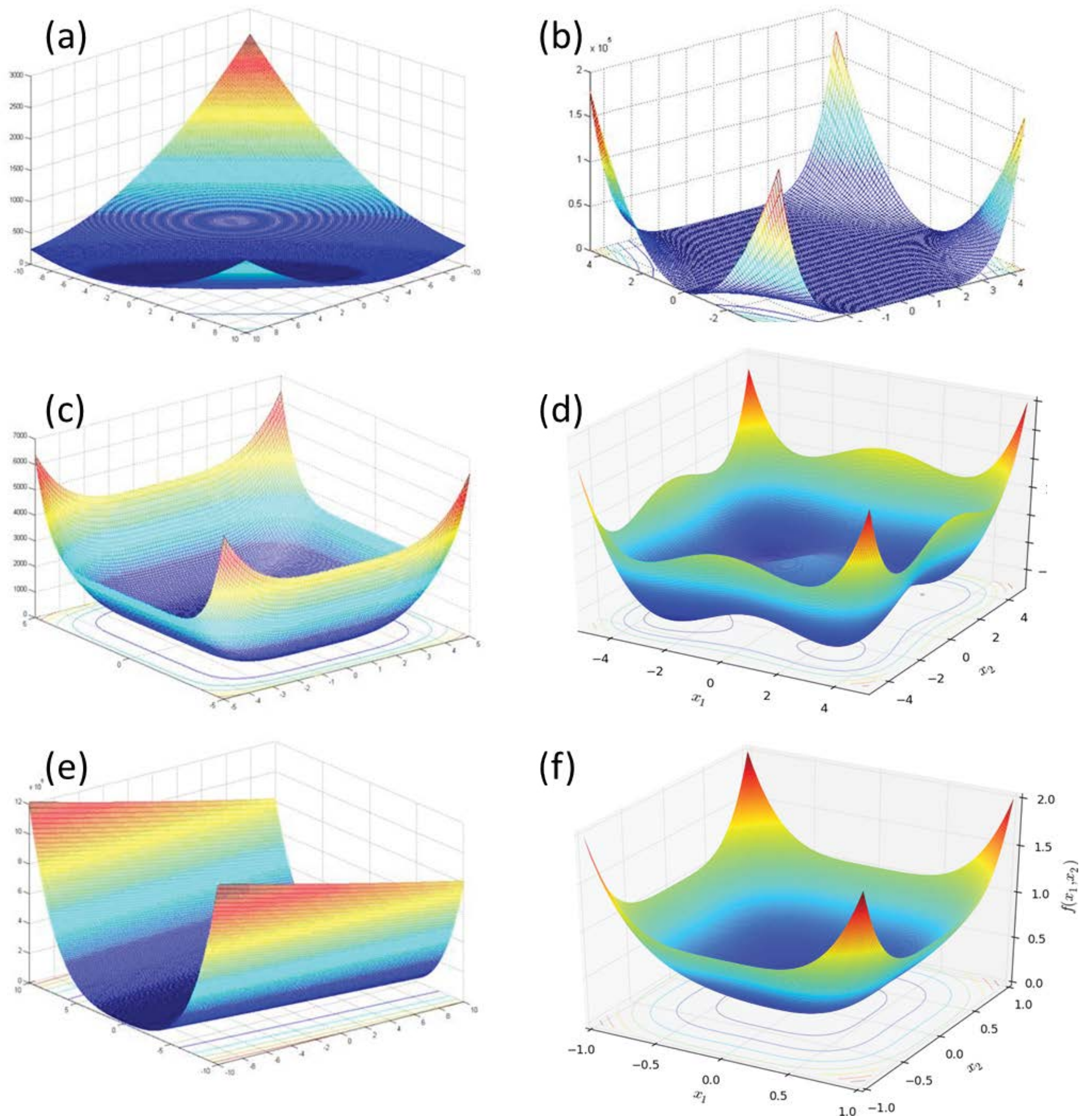
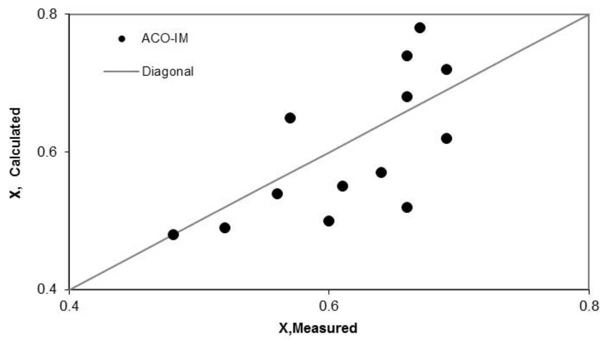


Fig. 5 Plots with global minima for functions (a) Quadratic (Booth), (b) Beale, (c) Hump, (d) Powerl quartic, (e) Rosenbrock and (f) Brown functions with varying degree of complexity.



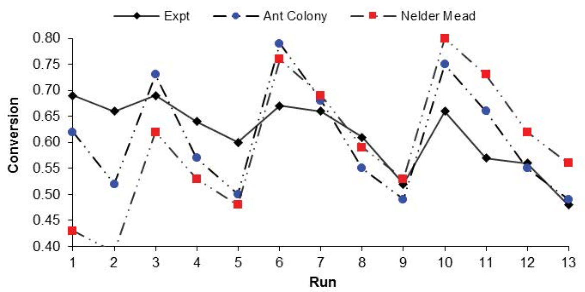


Fig. 6 Comparison of experimental and predicted substrate conversions with ACO and conventional Nelder mead optimization.

5.52 and 1.55 respectively. Using these optimal values, the substrate conversions are predicted using the mathematical, the quality of predictions with respect to experimental values and conventional Nelder-mead optimization(NMO) are shown in (Fig. 6). It can be observed that the quality of prediction of substrate conversion using ACO are far better than NMO.

CONCLUSION

Inverse estimation of model parameters of any process through scientific demonstrating course is an appealing contrasting option to the trial techniques. In this work, a novel streamlining strategy in view of a heuristic approach motivated by insect state scrounging conduct is executed for the assurance of parameters required in the film thickness and kinetic models of fixed bed anaerobic biofilm reactor. The outcomes are assessed concerning the numerical models, improvement techniques, film thickness and kinetic expressions. These outcomes prompted examine the thoroughness of numerical model, the sort of active and film thickness models to be utilized inside the biofilm reactor for its productive execution. The proposed optimization strategy can be effortlessly extended for the estimation of model parameters in different applications.

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