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Application of fuzzy inference system (FIS) coupled with Mamdani's method in modelling and optimization of process parameters for biotreatment of real textile wastewater

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ABSTRACT

A fuzzy logic-based diagnosis system was developed to optimize the process parameters for the decolourization of a real textile wastewater. A batch-scale colour removal experiment was conducted with a set of variable parameters of the process. The measured data of variables were implemented into the fuzzy inference system with Mamdani's method. The fuzzy model incorporates the weights provided by an expert, avoids the crisp values and offers overlapping range between the different fuzzy sets. A fuzzy rule-based model was shaped to define essential quality parameters monitored as pH, temperature, inoculum concentrations and glucose concentration as inputs. The fuzzy-modelled values of decolourization were validated against the experimental values. Results suggested that modelled results could be validated with experimental data-sets, as supported by a significant correlation coefficient (r = 0.87). This study confirms the applicability of fuzzy logic for optimization of conditions in the decolourization process in textile wastewater treatment process.

Keywords: Textile wastewater; Mixed culture; Fuzzy inference system; Optimization

1. Introduction

The major environmental problem associated with the textile mill wastewater is synthetic dyes. In general, chemical or biological treatment was applied for treatment of textile wastewater. The removal of dyes from effluents is an important problem, particularly for small-scale textile industries where working conditions and economic conditions are the major barrier in treating wastewater treatment prior to final disposal. The biological treatment may present a relatively inexpensive way to remove dyes from wastewater. Microbial process for decolourization and degradation is an environment-friendly and cost-competitive alternative process over chemical decomposition processes [1]. Much work has been done on the decolourization of dyes using pure cultures of microbes under growing condition in batch and continuous modes of operation. Single bacterial or fungal strains are effective in colour removal, but difficulty of this method is to maintain

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purity of the biological culture in the field conditions [2,3]. Thus, the application of mixed cultures in dye removal mechanism seems to be more promising for large-scale operation at field conditions. The interference of other constituents of wastewater is important in dye removal process during biological treatment of textile wastewater. The real textile mill wastewater, which is a mixture of a variety of toxicants and pollutants, affects the dye removal process in different ways. The valuable information on optimization of conditions for real textile mill wastewater biotreatment is not well described in the available scientific literature. In order to design a cost-effective remediation technique, the governing processes (physical, chemical and biological) need to be fully understood. Mathematical models are recognized as effective tools that could help to optimize the removal processes [4,5].

The term computing with words has been introduced by Zadeh [6] to explain the notion of reasoning linguistically rather than with numerical quantities. Fuzzy logic and fuzzy sets are effective tools for modelling complex mathematical problems with parameters that demonstrate uncertainty [7]. Fuzzy inference systems (FIS) can be used in a wide range of industrial and commercial control applications that require analysis of uncertain and imprecise information [8]. A fuzzy number describes the relationship between an uncertain quantity x and a membership function m, which ranges between 0 and 1. An element x belonging to a set A is defined as $x \in A$, and an element that is not a member in A is noted as $x \notin A$. A fuzzy set A is defined below in Eq. (1):

$$A = \{(x, \mu_A(x)) \mid x \in A, \mu_A(x) \in [0, 1]\} \quad (1)$$

where $\mu_A(x)$ is the membership function belonging to the interval [0, 1]. Fuzzy-based evaluation methods help in addressing deficiencies inherent in binary logic and are useful in propagating uncertainties throughout models.

The FIS consists of membership functions for state and control variables, production rules prepared from information provided by experienced operators and a fuzzy inference engine [9,10] successfully devised a methodology to assess the risk of water effluents from wastewater treatment plants based on fuzzy logic, and tested using the effluent's pollution data coming from 22 wastewater treatment plants. A novel water quality index based on fuzzy logic for routine assessment of surface water quality was developed by Gharibi et al. [11]. While [12] compared the binary and fuzzy logic-based model for river water quality assessment, [13] controlled aeration using fuzzy logic in an activated sludge wastewater treatment plant.

Therefore, the aim of this study was to develop fuzzy inference model to optimize techno-economic process parameters for decolourization of real textile wastewater using mixed biological culture. In this study, a fuzzy logic-based diagnosis system was developed to model the effect of variables (inputs) on the decolourization. The information of measured variables and the expert knowledge (EK) were implemented into the FIS with Mamdani's method by means of a fuzzy-based rule structure. Because of allowing a simplified representation and interpretation of the fuzzy rules, Mamdani's fuzzy inference method is the most commonly applied fuzzy methodology [14]. In this study, Fuzzy Logic Toolbox of MATLAB® R2012a was used to create and to edit the present FIS (Fig. 1).

2. Materials and methods

2.1. Textile wastewater

The real textile mill wastewater (untreated effluent) was procured from a local textile industry located in industrial area, Delhi. The effluent was collected in a large glass container of (20 L) capacity and brought to laboratory. In lab, the effluent was stored at 4˚C in a cold room, to be used for further experimentations. The characteristics of untreated textile wastewater are given in Table 1.

2.2. Aerobic mixed culture acclimatization and inoculum preparation

A primary requirement of the present work was to develop an acclimatized culture which can decolourize textile wastewater. Acclimatization was done in shake flasks in the presence of remazol black B (RBB) and methylene blue dyes. The textile sludge was used as a source of inoculum. For enrichment of the culture, the heterogeneous population was first grown aerobically in a medium containing 1% (w/v) glucose as the carbon and energy source and 25 mg/l RBB dye. During acclimatization period, the amount of glucose was regularly checked and maintained at 1%. The culture was gradually exposed to increasing concentrations of RBB dye in order to acclimatize the microbial culture to the higher concentrations of dye. Successive transfers of the culture into fresh glucose medium containing higher concentrations of RBB, up to 300 mg/l, were done at 37˚C. The duration of the acclimatization was around six months. This acclimatized microbial culture was used in all the experiments in the present study.

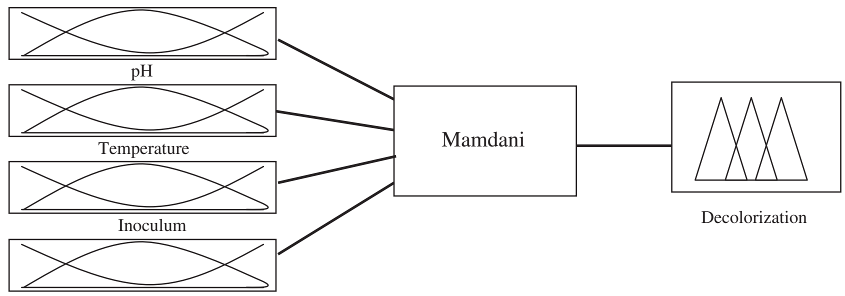


Fig. 1. FIS screen editor.

Table 1
Characteristics of the textile industry effluent

Sr. no	Parameters	Values
1	pH	8–10
2	Temperature ℃	38–40
3	TSS	180–200
4	TDS	3,700–3,900
5	COD	1,400–1,600
6	BOD	400–600
7	Oil and grease	10–12
8	Chloride	2,200–2,400
9	Trace elements (Fe, Zn, Cu, Ni and Mn)	15–20
10	TKN (as-N)	25–30
11	NO_3–N	5–10

2.3. Aerobic batch decolourization

The batch experiments were performed in batch reactors to examine the potential of the acclimatized mixed culture for the removal of colour from real textile wastewater. The removal of dye was examined with respect to changes in conditioning parameters: pH, temperature, glucose concentration and inoculum concentrations. Different sets of variations of parameters pH (5, 6, 7, 8 and 9), temperature (20, 30, 35, 45 and 55℃), glucose concentrations (0.25, 0.5, 1 and 2% w/v) and inoculum concentrations (5, 10, 15 and 20% v/v) were used to examine the colour removal from wastewater.

2.4. Analytical methods

To examine the periodic changes in different parameters, the wastewater samples were drawn at an interval from the batch reactor. The samples were centrifuged at 5,000 rpm for 10 min using centrifuge (Hitech model) to estimate the suspended biomass. Then, supernatant was analysed to estimate the concentration of dye using UV–visible spectrophotometer (Model: Systronic 117). All water analyses were performed using standard protocols as described by APHA [15]. All AR-grade chemicals and reagents were used while performing analytical tests.

2.5. Fuzzy model structure

A general fuzzy system has basically four components: membership function (fuzzification), fuzzy rule base, defuzzification and fuzzy outputs. In fuzzification, numerical inputs and output variables are converted into linguistic terms or adjectives and the corresponding degrees of the one or more several membership functions are determined [16]. It has been reported by Akkurt et al. [17] that fuzzy inference engine takes into account all the fuzzy rules in the fuzzy rule base and learns how to transform a set of inputs to corresponding outputs. Two kinds of inference operators, minimization (min) and product (prod), which are widely used in set theory (union and intersection), are basically employed in this step. The union and intersection of A and B can be defined as:

$$\mu_{A \cup B} = \max\{\mu_A, \mu_B\} \tag{2}$$

And

$$\mu_{A \cup B} = \min\{\mu_A, \mu_B\} \tag{3}$$

Finally, in the defuzzification step, linguistic results obtained from the fuzzy inference are translated into a real value using the rule base provided and centroid method was used. In this study, we selected trapezoidal and Gaussian-shaped membership functions for input and output variables for optimal software performance as shown in Fig. 2. A trapezoidal membership function is specified by four parameters given in Eqs. (4) and (5).

$$y = \text{trapmf } (x, [a, b, c, d]) \tag{4}$$

The function is described as:

$$y = \begin{cases} \frac{x-a}{b-a}, \ x \in (a, b) \\ 1, \ x \in (b, c) \\ \frac{d-x}{d-c}, \ x \in (c, d) \end{cases}$$

and

$$y = 0, (d \le x \le a) \tag{5}$$

A Gaussian membership function depends on two parameters and c as given in Eqs. (6) and (7).

$$y = \text{gaussmf}(x, \ [\text{sig } c]) \tag{6}$$

The function is described as:

$$f(x; \sigma, c) = e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{7}$$

The scalar parameters of membership functions were adjusted until satisfactory outputs were obtained with respect to the set of rules used in the study.

2.6. Statistical evaluation

The model results were statistically analysed using mean absolute percentage error (MAPE) given by Eq. (8).

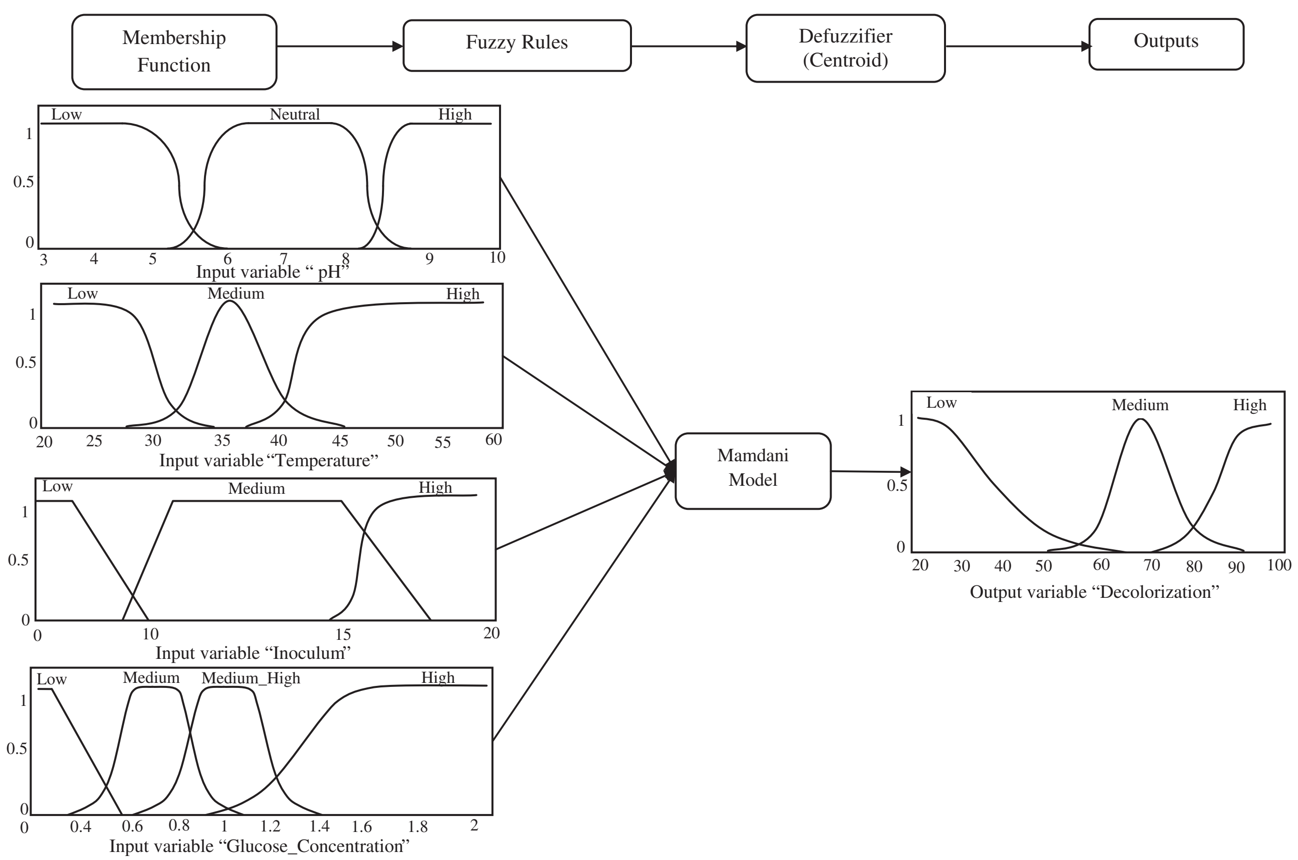


Fig. 2. Fuzzy model structure.

Table 2
Model configuration

Input/output parameter	Quantitative range	Linguistic variable
pH	<6	Low
	6–8	Neutral
	>9	High
Temperature	20–35	Low
	25–40	Medium
	>35	High
Inoculum	5–10	Low
	7–17	Medium
	>14	High
Glucose concentration	0–0.5	Low
	0.4–0.8	Medium
	0.75–1.25	Medium high
	1–2	High
Decolourization	20–60	Low
	50–90	Medium
	>70	High

$$\text{MAPE } \% = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_p - x_i}{x_p}\right| \times 100\% \tag{8}$$

where x_p is the measured value, x_i is the value of the FIS structure, i: {1, 2, 3, ….n}, n is the total number of data in the data-set. The mean absolute percentage error is 12.44% which is under the acceptable limits.

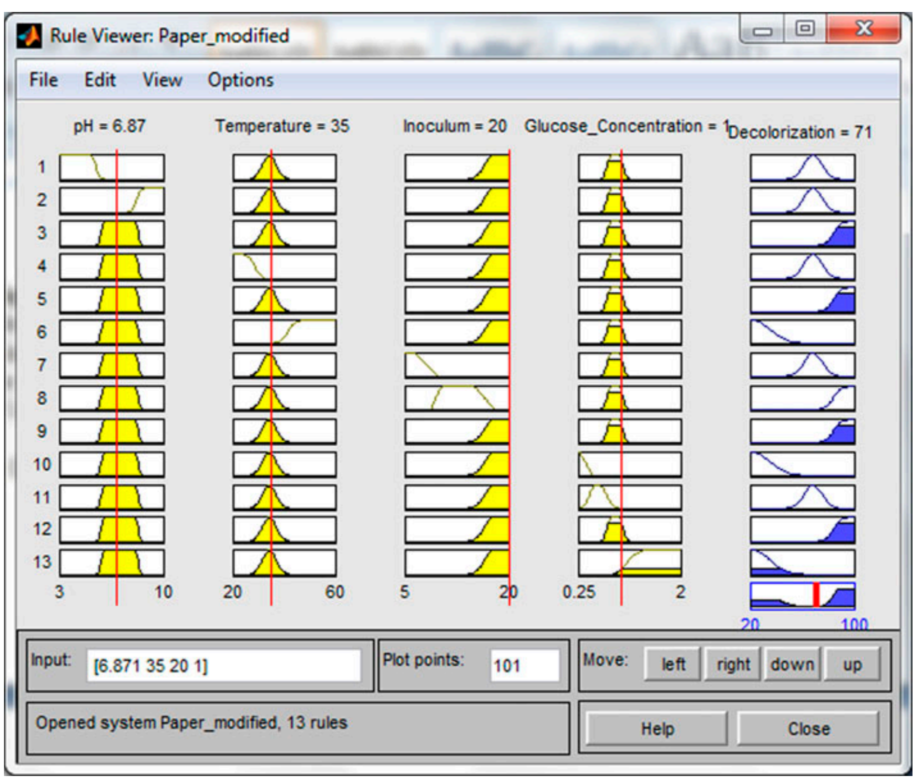
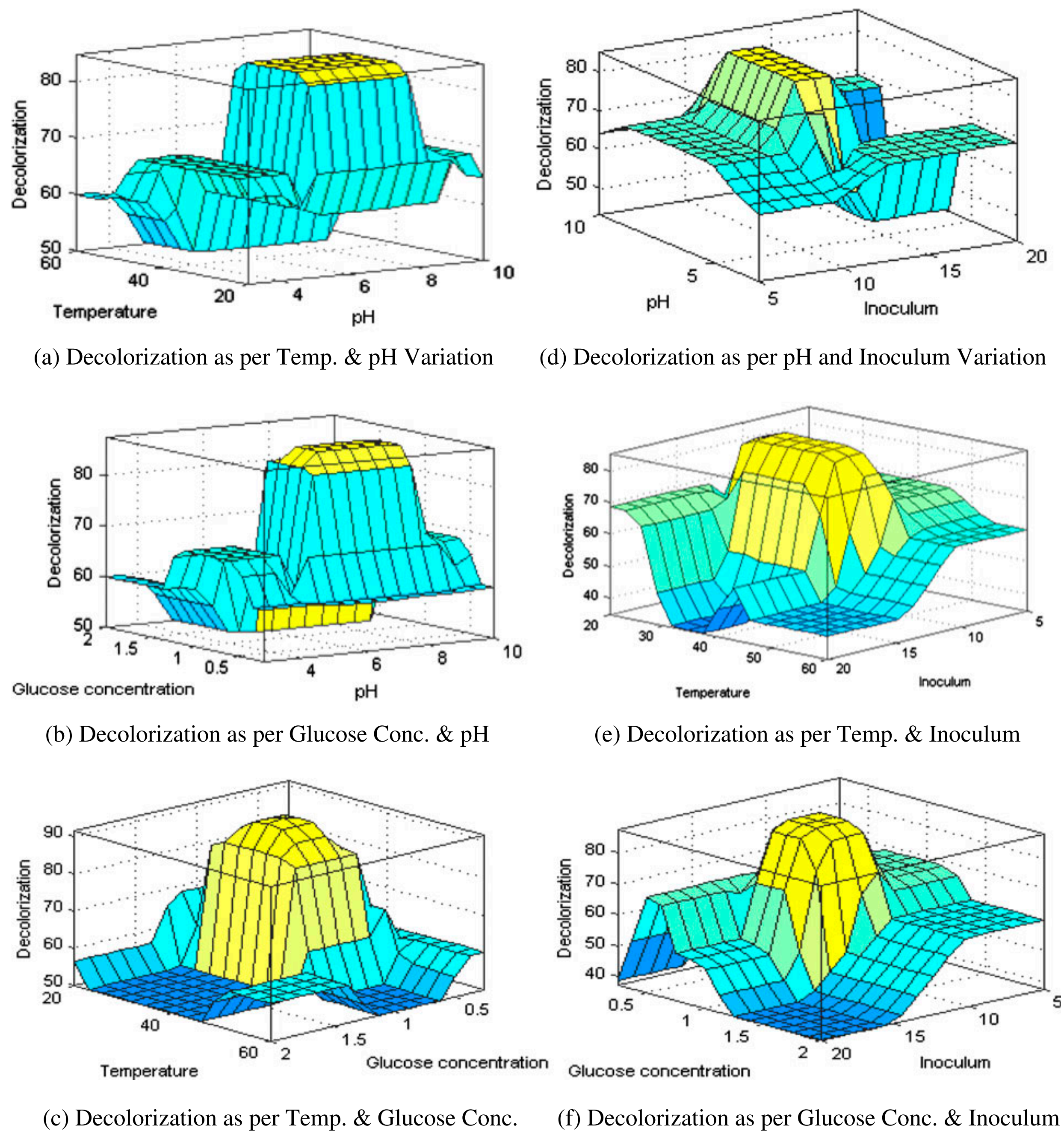


Fig. 3. Rule viewer screen to obtain defuzzified results.

3. Results and discussion

The model configuration (as described in Table 2) was structured as a result of EK implementation. Fuzzy rule-based modelling is discussed by establishing *if–then* rules using experimental data. The fuzzy sets, in the present study, were defined by the linguistic terms low, medium, medium high and high. Each parameter was assigned to one of the four fuzzy sets in terms of membership functions. The combinations of these process parameters given in Table 1 provide a basis for the development of rules. Fuzzy rule base unit contains all of the rules writeable in logical IF–THEN expression connecting input variables to output variables in the database. The rule viewer screen for defuzzified results is illustrated in Fig. 3. For rule formations, all possible intermediate (fuzzy



(a) Decolorization as per Temp. & pH Variation

(d) Decolorization as per pH and Inoculum Variation

(b) Decolorization as per Glucose Conc. & pH

(e) Decolorization as per Temp. & Inoculum

(c) Decolorization as per Temp. & Glucose Conc.

(f) Decolorization as per Glucose Conc. & Inoculum

Fig. 4. 3D response surface for decolourization of textile wastewater by consortia as a function of different variables.

set) connections between inputs and outputs are taken into consideration. The rule base was formed after assignment of the memberships. In the rule base, the rules were written in "If x is A and y is B, then z is C" format, e.g. "IF pH is High or Temperature is High or …. THEN pH is high".

The fuzzy model was validated using the experimental data of the all input variables. Experimental data show that the decolourization increases with increase in pH from 5 to 7 and then decreased with further increase in pH up to 9.0. The maximum decolourization (88%) was recorded at pH 7. The percentage decolourization at pH 6 and 8 was 84 and 85%, respectively. The percentage decolourization at pH 5 and 9 was relatively low 60 and 62%, respectively. The fuzzy outputs, as illustrated in Fig. 4(a), (b) and (d), indicate that the maximum decolourization should be obtained at pH 6 and 7, corroborating with the experimental results. pH has a major effect on the efficiency of dye decolourization, and the optimal pH for colour removal is often between 6.0 and 10.0 [18]. The pH tolerance of decolourizing bacteria is quite important because reactive azo dyes bind to cotton fibres by addition or substitution mechanisms under alkaline conditions and at high temperatures [19].

The experimental results of the batch trials with different inoculum strengths (5—20% v/v) indicate that percentage decolourization increases with respect to increasing inoculum strengths, although no significant difference was recorded with 10, 15 and 20% inoculum strengths in decolourization rate at the end. The fuzzy outputs suggested the maximum decolourization at 20% inoculum strengths which is in agreement with experimental data (Fig. 4(d)–(f)). The impact of temperature on colour removal was also significant in this study. The experimental data show that percentage decolourization increased from 66% to 88% with increase in temperature from 20 to 30˚C, respectively; thereafter, a trend of decreasing removal with respect to increasing temperature was recorded (e.g. 27% removal with 55˚C). The fuzzy outputs suggest the maximum removal with temperature ranges of 25–35˚C which is corroborated by experimental results (Fig. 4(a), (c) and (e)). Decolourizing activity was significantly suppressed at higher temperature, which might be due to the loss of cell viability or deactivation of the enzymes responsible for decolourization at higher temperatures [20,21]. The impact of glucose concentrations (0.25—2%) on colour removal process was also evaluated. A trend of increasing decolourization with respect to increasing glucose concentrations (i.e. 48–90% with 0.25–1%, respectively) was recorded in this study. However, lower percentage decolourization observed at lower glucose concentration could be due to the fact that glucose concentration was not adequate for sufficient microbial growth required to cause significant decolourization. The fuzzy outputs depicting glucose concentration indicate the least impact of glucose over decolourization rate (Fig. 4(b), (c) and (f)). The experimental and fuzzy output suggests the maximum decolourization at 1% glucose concentration, which validates the fuzzy model. The fuzzy model was validated using the experimental data of all input variables and the relationship between modelled value and experimental value was validated using linear correlation analysis (Fig. 5). Results, thus, show a significant correlation between measured and modelled values (r = 0.87).

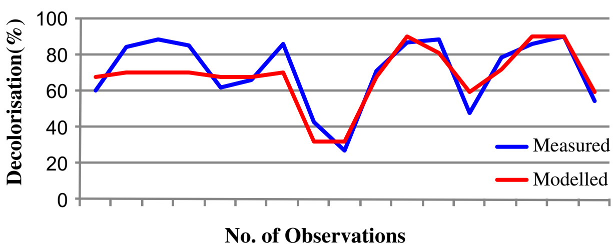


Fig. 5. Measured and fuzzy-modelled values of decolourization.

4. Conclusions

In the present study, the decolourization of real textile wastewater using mixed culture was modelled using a fuzzy-based system. The outputs of model have revealed that the optimum process variables for the maximum decolourization could be predicted with a high degree of accuracy. The fuzzy-modelled values of decolourization show a close accuracy with the experimental data-sets. The calculated errors remained at 12.4% level, which falls within the acceptable limits as the analytical error intervals are much higher in the measurements of these parameters (generally 10–20%). Results of the optimum stage confirmed the applicability of this evolutionary computational technique for optimization of conditions in the decolourization process.

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