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Short communication

# Optimization of conditions (pH and temperature) for *Lemna gibba* production using fuzzy model coupled with Mamdani's method

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ABSTRACT

A fuzzy-logic-based diagnosis system was developed to determine the effect of pH and temperature on duckweed *Lemna gibba* biomass production. The measured data of variables were implemented into the fuzzy inference system (FIS) with Mamdani's method. A fuzzy rule-based model was shaped to define the essential quality parameters monitored as pH and temperature as inputs. The fuzzy modeled values of biomass gain were validated against the experimental values with a strong correlation ($r^2$) of 0.98.



## 1. Introduction

The volume of wastewater generated by domestic, industrial and commercial sources has been increased with reckless developmental activities and human population explosion. The proper treatment strategy can play a very crucial role in tackling wastewater management aspects (Brix and Schierup, 1989). The conventional wastewater treatment system involves a series of treatments such as, preliminary treatment (screening and grit removal); primary treatment (screening, sedimentation); secondary treatment (activated sludge process, oxidation ponds, fluidized bed reactors) and tertiary treatment (sand filters, UV lamps, chemical precipitation) based upon the various physical, chemical and biological processes (Metcalf and Eddy, 2004). But, this conventional system offers several limitations on management and technological ground (as involves huge investment, labor, energy, operating and maintenance costs). So there is need of technology with low inputs and environmentally safe mechanism. The potential of duckweed in wastewater treatment has become well evident in the recent time. The duckweed based wastewater treatment system is a low cost, less technical in maintenance and operation, user friendly and effective in terms of results and can contributes toward water sustainability (Bal Krishna and Polprasert 2008; Azeez and Sabbar, 2012; Verma and Suthar, 2014). Apart from removing pollutants from wastewater this duckweed system offers huge quantity of plant biomass at the end which can be harvested as feedstock for animal and bioenergy production (Verma and Suthar, 2014). The remediation capacity of plant in general is linearly correlated with the biomass productivity of the system. The biomass production is directly affected by few key abiotic factors like: pH, temperature, photoperiod etc. By manipulating such parameters, the productivity of the system can be enhanced and hence, the removal potential can be improved (Papadopoulos and Tsihrintzis, 2011; Khellaf and Zerdaoui, 2013). The accumulated duckweed being rich in carbohydrate, protein and starch may be utilized as bioenergy feedstock or livestock feed (El-Shafai et al., 2007; Cheng and Stomp, 2009). The information regarding optimization of operational conditions for duckweed based wastewater treatment system and biomass production is not well described in available scientific literature.

Fuzzy modeling based on fuzzy implication and reasoning is one of the most important fields in mathematical modeling (Takagi and Sugeno, 1985; Kosko, 1992; Scannapieco et al., 2012). Fuzzy logic and fuzzy sets are effective tools for modeling complex mathematical problems with parameters that demonstrate uncertainty (Scannapieco et al., 2012; Kotti et al., 2013). This approach has proved very useful in medical diagnosis (Lascio et al., 2002), information technology (Lee, 1996), water quality (Lu et al., 1999), reliability analysis (Sadiq et al., 2004) and many other industrial applications (Lawry, 2001), where reported data are either qualitative and decision-making is performed based upon expert opinions. Fuzzy sets are the sets with boundaries that are not

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precise and the usage is not a matter of affirmation or denial, but rather a matter of degree. 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 $x \in A$, an element that is not a member in $A$ is noted as $x \notin A$. A fuzzy set $A$ is given in Eq. (A.1).

$$A = \{(x, \mu A(x)) \mid x \in A,\ \mu A\ (x) \in [0,1]\} \tag{A.1}$$

where $\mu_A\ (x)$ is a 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.

Fuzzy inference systems have found a wide range of industrial and commercial control applications that require analysis of uncertain and imprecise information (Horiuchi et al., 1993; Akcayol, 2004). In this study, a fuzzy-logic-based diagnosis system was developed to study the effect of variables (inputs) on biomass production in a duckweed pond system. The information of measured variables and the expert knowledge (EK) were implemented into the fuzzy inference system (FIS) with Mamdani's method by means of a fuzzy-based rule structure. The Fuzzy Logic Toolbox of MATLAB® R2012a was used to create and to edit the present Fuzzy Inference System.

## 2. Material and method

### 2.1. Experimental design

The duckweed *L. gibba* was collected from a local freshwater body located nearby the University Campus. The collected material was washed in tap water to remove adhering silt and other substances and then sterilized using 1% NaClO for 3–5 min. Then plant material was transferred to pre-sterilized container with 1/10 diluted Hoagland solution for further propagations to get contamination-free second generation of plants (Penningsfeld and Kurzman, 1975; Eliasson, 1978). The composition of Hoagland's solution was (all in mg/L): $KNO_3$, 1515.0; $KH_2PO_4$, 680.0; Ca$(NO_3)_2 \cdot 4H_2O$, 1180.0; $MgSO_4 \cdot 7H_2O$, 492.0; $ZnSO_4 7H_2O$, 0.22; $H_3BO_3$, 2.85; $Na_2MoO_4 \cdot 2H_2O$, 0.12; $CuSO_4 \cdot 5H_2O$, 0.08; $MnCl_2 \cdot 4H_2O$, 3.62; $FeCl_3 \cdot 6H_2O$, 5.4; tartaric acid, 3.0 (Hoagland and Arnon, 1950). The culture media was renewed twice every week. The prominent and healthy plants were hand sorted to be used for experimental trials. The duckweed culture was maintained under ambient temperature of 24 °C (SD = 2) and light/dark regime of 16/8 h. The effect of pH, temperature and light regime on duckweed growth and biomass production has been assessed. The six different ranges of pH (i.e. 2, 3, 5, 7, 9 and 11) and three different temperatures range (10 °C, 25 °C and 35 °C) were taken to design different experimental set-ups. The pH of the media was adjusted using 1N solution of HCl and NaOH. The experimental set-ups were prepared using glass beakers of 500 ml capacity. The Hoagland's media were used as growth medium to support the growth of duckweed (0.5 g) that was inoculated in each experimental set-up. The influence of experimental condition on plant growth was assessed at the end of seventh day considering frond number and biomass gain. All experimental set-ups were established in triplicates and average of all the three observations was used to express the result.

### 2.2. Analytical methods

The frond number of *L.gibba* was calculated manually using strainer. The final weight was determined by weighing harvested duckweed at the end of seventh day. Experiments were carried out in triplicates and data were averaged with standard deviation (SD). SPSS® statistical package (Window Version 13.0) was used for data analysis. All statements reported in this study are at the $p < 0.05$ levels. The further optimization has been done using Fuzzy Logic Toolbox of MATLAB® R2012a.

### 2.3. Model structure and configuration

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 (Altunkaynak et al., 2005). Akkurt et al. (2004) have reported 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

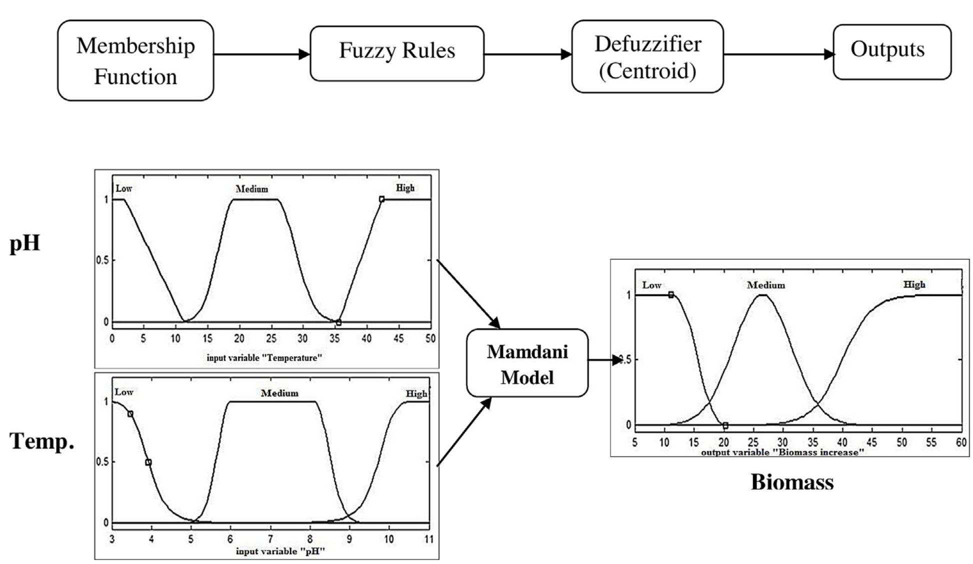


**Fig. 1.** Fuzzy model structure

intersection of $A$ and $B$ can be defined by Eqs. (B.1) and (B.2) as:

$$\mu_{A\cup B} = \max\{\mu_A, \mu_B\} \tag{B.1}$$

$$\mu_{A\cap B} = \min\{\mu_A, \mu_B\} \tag{B.2}$$

Finally, in the defuzzification step, linguistic results obtained from the fuzzy inference are translated into a real value by using the rule base provided (Bıyıkoğlu et al., 2005). This phase is responsible for transforming the fuzzy results from the fuzzy system into crisp values (Kusan et al., 2010). In this study, we employed centroid method which is most commonly used defuzzification technique. In this study, we selected trapezoidal and Gaussian shaped membership functions for input and output variables for optimal software performance as shown in Fig 1. A trapezoidal membership function is specified by four parameters given by Eqs. (C.1) and (C.2):

$$y = \text{trapmf}\,(x,[a\ b\ c\ d]) \tag{C.1}$$

The function is described as:

$$y = \begin{cases} \dfrac{x-a}{b-a}, & x \in (a,b) \\ 1, \ x \in (b,c) & \text{and} \quad y = 0, (d \le x \le a) \\ \dfrac{d-x}{d-c}, & x \in (c,d) \end{cases} \tag{C.2}$$

A Gaussian membership function depends on two parameters $\sigma$ and $c$ as given by Eqs. (C.3) and (C.4):

$$y = \text{gaussmf}(x,\ [\text{sig}\ c]) \tag{C.3}$$

The function is described as:

$$f(x;\sigma,c) = e\frac{-(x-c)^2}{2\sigma^2} \tag{C.4}$$

The scalar parameters of membership functions were adjusted until satisfactory outputs were obtained with respect to the set of rules used in the study (Fig. 1).

### 2.4. Statistical evaluation

The model results were statistically analyzed using mean absolute percentage error (MAPE) given by Eq. (D.1).

$$\text{MAPE\%} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_p - x_1}{x_p}\right| \times 100\% \tag{D.1}$$

where, $x_p$ is measured value, $x_i$ is value of the FIS structure, $i$: {1,2,3 . . . $n$}, $n$ is the total number of data in the dataset. The mean absolute percentage error is 14.88% which is under the acceptable limits.

## 3. Results and discussion

The fuzzy model as configurated was given in Table 1. The *if–then* rules were established using experimental data and the output framed as fuzzy rule-based modeling. The Table 1 provides a selection basis for the development of rule base. Fuzzy rule base unit contains all of the rules writeable in logical if–then expression connecting input variables to output variables in the database. All possible intermediate (fuzzy set) connections between inputs and outputs are taken into consideration while writing these rules. 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 is validated using the experimental data (17 readings) of the all input variables. The data available after experimentation validated that pH significantly influences the plant growth dynamics. The duckweed growth showed increment with increasing pH in the medium. The pH shift toward alkaline range further decreases growth. The maximum biomass gain of 51.3% was witnessed at 7 pH. Likewise, both at low (10 °C) and high (35 °C) temperature, the duckweed plant growth showed significantly decrement. The maximum biomass gain of 55% was observed at 25 °C. The fuzzy output, as illustrated in Fig 2 indicates that the maximum duckweed growth can be achieved at pH 7 and temperature 25 °C corroborating with the experimental results. The fuzzy model was validated using the experimental data of all input variables and relationship between modeled value and experimental value was validated using linear correlation analysis (Fig. 3). The results are found to be satisfactory with a strong

**Table 1**
Model configuration.

| Input/output parameter | Quantitative range | Linguistic variable |
|---|---|---|
| pH | 3–5 | Low |
| | 5–9 | Medium |
| | 9–11 | High |
| Temperature | 0–11 | Low |
| | 11–35 | Medium |
| | >35 | High |
| Growth | 5–20 | Low |
| | 11–40 | Moderate |
| | >35 | High |

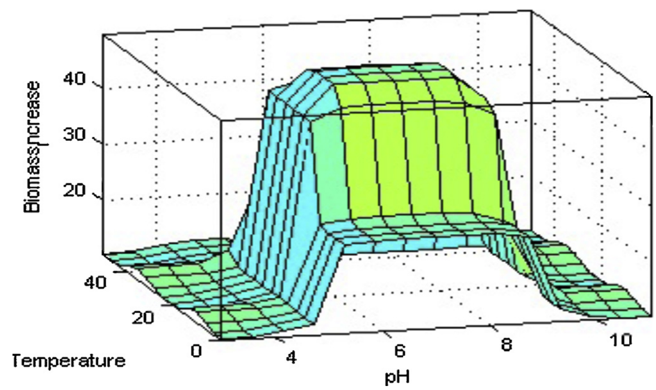


**Fig. 2.** 3D response surface for duckweed biomass gain

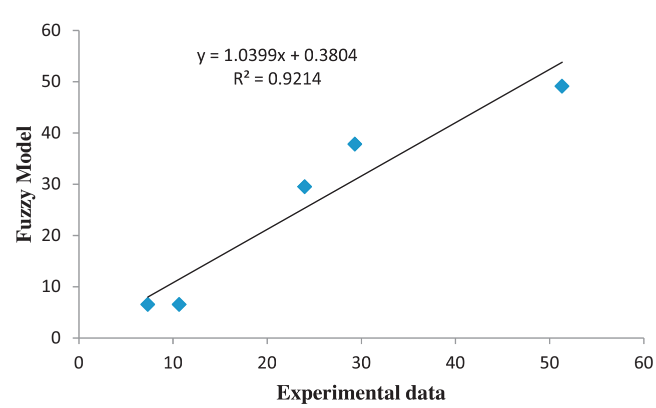


**Fig. 3.** Interrelationship between experimental and modeled values.

coefficient of correlation ($r^2$) between measured and modeled values to be 0.98. The results thus, suggested that fuzzy models can be applied for optimization of conditions of major parameters for culturing of duckweed biomass at industrial scale.

## 6. Conclusions

The proposed FIS approach is effective and reliable for extracting features from input data in combination with EK. The calculated errors remained at 14.88% level, which falls within the acceptable limits as the analytical error intervals are much higher in the measurements of these parameters (generally 10–20%). The fuzzy approach offers advantages such as ease of tuning and its adaptive capabilities, even in the presence of a highly nonlinear dynamics among the variables. The model can respond input values that have not been involved in the initial data. Therefore, this structure does not require the separation of training and test data set. The results validated that the adequacy of proposed mathematical model in optimization of growth regulating conditions of duckweed plant.

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