# Fuzzy Logic based Fed Batch Fermentation Control Scheme for Plant Culturing

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***Abstract*—Biotechnological plants, such as Fed Batch Fermentation (FBF) systems used in plant culturing, have an abundance of uncertainty and complexity, which makes it difficult to model these systems and unsuitable to employ conventional techniques for control design. Recently, artificial intelligence and computational intelligence techniques have been employed in modelling and controlling these systems. However, most of the techniques employed are hybrid models which have high computational requirements. In this study, a conventional Fuzzy Logic Controller (FLC) for FBF control is presented with the aim of improving efficiency. The fermentation plant is modelled as a black box using C programming language. The FLC is designed and simulated in MATLAB and the results are compared with a nominal feeding profile. The FLC resulted in a 137 percent increase in product concentration, a 538 percent improvement in productivity, and a 14 percent increase in volume. The nominal profile, on the other hand, performed better in terms of Biomass, with the FLC providing a 70% decrease in Biomass levels of the fermentation process.**

**Keywords— Artificial Intelligence, Fed Batch Fermentation, Fuzzy Logic Controller, Nominal Profile, Plant Tissue Culture.**

## I. INTRODUCTION

Fed batch culture is a widely used technique for achieving high cell density in plant or microbial cultures by controlling the nutrient feeding rate, which is frequently required for high product productivity [1]. The fed batch technique is used to overcome substrate inhibition or catabolite repression by intermittently feeding the substrate to the reactor, as no substrate is removed during the process [2]. This technique is also usually used for hairy root cultures for the increased production of secondary metabolites. However, the productivity of the fed batch culturing of plant cells can be hampered since plant cell cultures consist of many kinds of medium components (Sugars, vitamins, plant growth regulators and salts). Plants are cultured in vitro in a variety of ways, including the fed batch process, which is carried out in fermenters (bioreactors).

Biotechnological systems, such as Fed Batch Fermentation (FBF) systems, have an abundance of uncertainty and complexity. This makes them difficult to describe, model and subsequently control [3]. Other technological processes are difficult to describe due to the complex nature of the systems, non-linearity, and complex measurement of critical variables. Because of these factors, information about these systems can only be obtained through experimentation [4]. Fermentation necessitates a number of biological and biochemical processes, and there are hundreds of state variables due to the large number of metabolic byproducts and cell states [5]. The fermentation process and performance are far too complex to model. As a result, similar non-linear processes are controlled in an open loop, resulting in low productivity and excessive material use.

Recent advancements in the intelligent control of these FBF systems have resulted from the use of neural networks, fuzzy logic, and computational intelligence in modeling and control [2]. However, majority of existing methods are hybrid techniques which combine two or more intelligent models, which in turn leads to high computational demands. Fuzzy modeling is an appropriate black box nonlinear modeling technique that can be effective in systems where data is obtained experimentally and the structure is not well defined [4]. Thus, Fuzzy Logic modelling and control can be implemented as a stand-alone method which can provide satisfactory results with a reasonable computational cost.

In this study, an FBF regulation process using a Fuzzy Logic Controller (FLC) is presented in order to optimize the productivity of the fermentation process. To maximize productivity, a black box model was used to represent the plant, and an FLC was developed to control the system. The rest of this paper is distributed into four parts. Part 2 gives a literature review and related works, while part 3 presents the research methodology. Part 4 provides the findings of the research, while part 5 concludes the paper.

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## II. LITERATURE REVIEW

In the field of FBF control, there exists several studies. For instance, Soufian et al., [2] developed a fermentation process control technique based on adaptive clustering and computational intelligence The results showed that the intelligent techniques (Genetic algorithm-based Fuzzy Logic and Fuzzy Neural Network), which both modified the adaptive clustering inclusion, produced more biomass concentration than the techniques that did not.

In addition, Rincon et al., [6] developed an improved robust adaptive controller for an FBF bioreactor. This technique had input saturation and unknown varying control gain via dead-zone quadratic forms. The results showed the process was able to avoid excessive increase of updated parameters, tracking error convergence, and tracking error bounding.

Furthermore, Kim et al., [3] presented a model based reinforcement learning and predictive control technique. This method was applied to a two stage FBF reactor for optimal control. The results indicated that the proposed method was reliable and maintained high performance under the disturbances.

Similarly, an adaptive control scheme based on fuzzy logic of Specific Growth Rate (SGR) in fed batch process was presented in Butkus et al., [5]. The FLC controlled the SGR of a fed-batch process and was applied to a model of *Escherichia coli* cultivation process. The results showed that the algorithm was suitable to control the SGR in the biotechnological process.

Wu et al., [7] developed an optimal feedback control scheme using switched dynamical system method. This technique was applied to a class of FBF processes and the numerical results justified the effectiveness of the technique.

Additionally, in Dong et al., [8], an optimal control hybrid scheme for FBF was presented. The study utilized a nonlinear hybrid dynamic technique and a corresponding linear variation solution to study the strong stability of the system. The results proved the strong stability by the boundedness provided by the technique developed.

Furthermore, Zheng et al., [9] applied a gradient-free optimisation algorithm to enhance yield in an FBF system. The system utilized adaptive Particle Swarm Optimisation (APSO) and Simulataneous Perturbation Stochastic Approximation (SPSA) to optimize a penicillin fermentation process. The results showed the APSO outperformed the SPSA in terms of optimality, however, the SPSA performed better in terms of optimal cost.

From the aforementioned reviews, it can be observed that majority of the works with improved performance rely on hybridized models and these combined techniques have high computational requirements. Thus, the major contribution of this endeavor is to develop a conventional Fuzzy Logic Controller (FLC) to optimise a FBF process. The choice and justification of the FLC lies in its self-adapting capabilities, which allows it to maintain a desirable closed loop performance by learning about changes that may impact the plant's behavior [10]. This in turn provides optimum performance with reasonable computational requirements. The output of the FLC is the feeding profile which will be fed into the plant to produce an output. The results of the FLC performance are compared with the nominal controller for performance evaluation.

## III. RESEARCH METHODOLOGY

### *A. Process Description*

Fermentation is typically accomplished through three methods: batch, fed batch, and continuous. In the batch process, all materials are sited into the reactor at the beginning of the fermentation process, and the reactor has no input or output. There are both inputs and outputs to the reactor in the continuous category. Nothing is taken out of the reactor during the fed batch process; however, a substrate component is intermittently added to regulate the reaction [11]. The primary control goal of a fed batch fermenting process is to determine the proper feeding rate for the substrates, which facilitates both biomass and product concentration [2]. Fed batch methods are commonly employed in the biotechnology sector since they merge the benefits of continuous and batch operations. The method begins as a batch process, then the substrate is added until a practical restriction prevents the process from continuing [12]. The result of the FBF process is a mass of plant cells or secondary metabolite depending on the desired end product. For growth and production, two substrates are necessary [2].

For this work, the FBF process is represented as a black box model that varies with time. Because the process's beginning states and parameters randomly fluctuate from batch to batch, the exact output sequence cannot be created each time for the same input sequence [2]. The black box has a specified set of inputs, outputs, and limitations. The process's inputs are two substrate feed rates, u1 and u2. These feed rates are employed to supply substrates to the culture which results in the production of a secondary metabolite. The substrates are complementary in the sense that feeding only one of them yields no yield and feeding only one of them yields low yield. The process produces biomass, substrate 1, substrate 2, product concentration, and volume, which are denoted by the letters x, s1, s2, p, and v, respectively. Fig. 1 depicts a typical fed batch procedure.

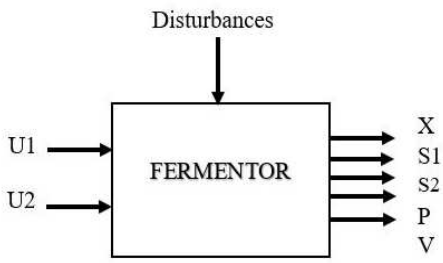


Fig. 1. A Typical FBF Process

U1 and U2 are the two inputs to the FBF process. Based on a nominal feeding profile, these inputs are the feed rates of substrates S1 and S2. Equations 1 and 2 yield the nominal feeding profile. However, the suggested feeding profile is insufficient for output. As a result, the developed controller is supposed to provide a regulated feed rate depending on the outputs in order to optimize the FBF process's performance. The process produces biomass (X), substrates (S1 and S2), product concentration (P), and volume (V).

$$U1 = 10 + \frac{25}{1 + e^{5-0.1t}} \quad (1)$$

$$U2 = 3.5 * \frac{1-1}{1 + e^{10-0.15t}} \quad (2)$$

The process is constrained by the maximum reactor volume (v_maximum = 4000) and maximum feed rates (f_maximum = 50). The process's cost function is productivity (J), which is described in terms of volume, product concentration, and fermentation period (T), which is not fixed (as shown in Equation 3).

$$J = \frac{P*V}{T} \quad (3)$$

Fig. 2 depicts the control system representation. The product concentration is the controlled parameter in this investigation (P). The setpoint is used as the process's input, and the error is calculated as the difference between the setpoint and the output (P). This error is sent into the fuzzy logic controller, which generates a regulated output in terms of feed rates (U1 and U2). The controller's output is sent into the fermentation plant, which creates the process's outputs (X, S1, S2, P and V).

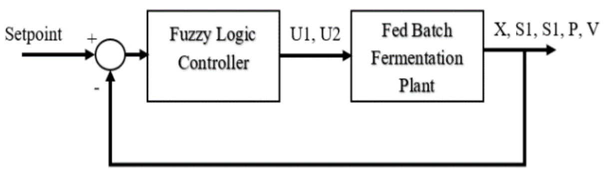


Fig. 2. FBF Control System

A C-Program function represents the plant. The plant is intricate, time-varying, and nonlinear. As a result, given the same input sequence, the same output cannot be achieved. This makes obtaining a model as a transfer function, state space representation, or differential equation problematic. As a consequence, the plant is called in MATLAB using a mex function each time. The fuzzy logic controller's output (the regulated feed rates) is fed into the plant, which provides the output values.

### B. *Fuzzy Logic Controller Design*

The Mamdani Fuzzy Inference System (FIS) was created in this work utilizing the Fuzzy Logic Toolbox in MATLAB (version R2019a). In terms of product concentration, the FIS had two inputs (error and change in error). The feed rates (U1 and U2) for substrates S1 and S2 are the FIS outputs. For defuzzification, the centroid approach was utilized.

In this investigation, the trapezoidal Membership Function (MF) was applied. Both inputs ranged from 0 to 3000, with values of vlow, low, med, high, and vhigh. U1 had a range of 0 to 30 with values of vlow, low, med, high, and vhigh. U2 output ranged from 0 to 10, with low, medium, and high levels. Fig. 3 and Fig. 4 show the membership functions for the input variables, whereas Fig. 5 and Fig. 6 depict the MFs for the output variables.

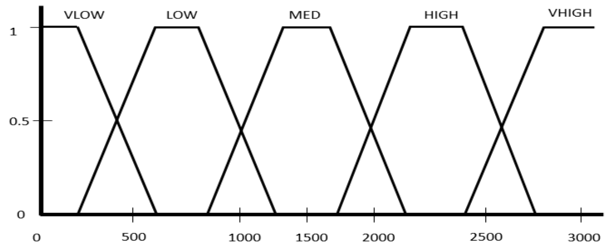


Fig. 3. MF for Error

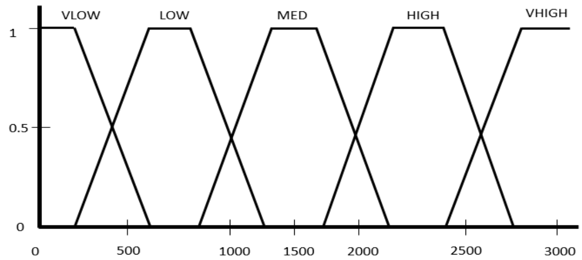


Fig. 4. MF for Change in Error

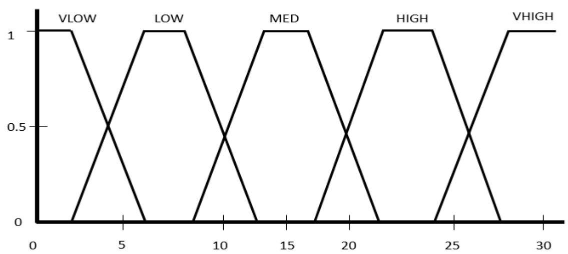


Fig. 5. MF for U1

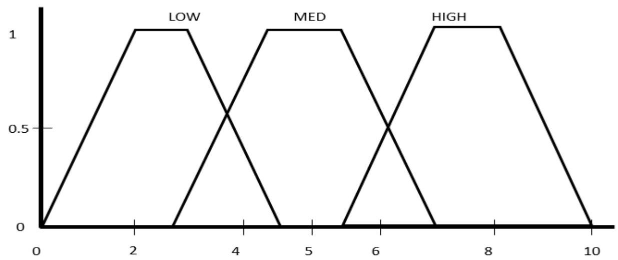


Fig. 6. MF for U2

The fuzzy rules used for feed rates U1 and U2 are presented in Tables I and II, respectively. The fuzzy rules were created with the goal of maximizing product concentration, which is the controlled variable. The plant model revealed that low U1 values resulted in increased product concentration and moderate volume values. Based on this fact, fuzzy rules were created to maximize product concentration while maintaining relatively high volume levels. This is due to the fact that reduced volume levels result in poorer production, which is undesirable.

TABLE I. FUZZY RULES FOR FEED RATE (U1)

| **Error/ Change in Error** | **VLOW** | **LOW** | **MED** | **HIGH** | **VHIGH** |
|---|---|---|---|---|---|
| **VLOW** | MED | MED | LOW | VLOW | VLOW |
| **LOW** | MED | MED | LOW | VLOW | VLOW |
| **MED** | MED | MED | MED | MED | MED |
| **HIGH** | VLOW | VLOW | VLOW | VLOW | VLOW |
| **VHIGH** | VLOW | VLOW | VLOW | VLOW | VLOW |

TABLE II. FUZZY RULES FOR FEED RATE (U2)

| **Error/ Change in Error** | **VLOW** | **LOW** | **MED** | **HIGH** | **VHIGH** |
|---|---|---|---|---|---|
| **VLOW** | MED | MED | LOW | LOW | LOW |
| **LOW** | MED | MED | LOW | LOW | LOW |
| **MED** | MED | MED | MED | MED | MED |
| **HIGH** | LOW | LOW | LOW | LOW | LOW |
| **VHIGH** | LOW | LOW | LOW | LOW | LOW |

## IV. RESULTS

The plant and the Fuzzy Logic Controller (FLC) were both simulated in MATLAB (R2019a). The plant is a C-programming language black box model. To establish an interface between MATLAB and the plant, a mex (MATLAB extension) file was generated (C program). The nominal profile was compiled in the C programming language to produce a data file holding the compilation results. The MinGW-64 compiler was utilized in this investigation as the C compiler. To achieve fuzzy controller results, the FLC was constructed and executed in MATLAB. For performance evaluation, the FLC data were compared to the nominal profile.

The FLC receives error and change in error as inputs, which are assessed in terms of the controlled variable (product concentration). The FLC outputs are the feed rates for substrates 1 and 2. (U1 and U2). Fig. 7 and Fig. 8 compare the feed rates U1 and U2 derived from the FLC to the feed rates of the nominal profile.

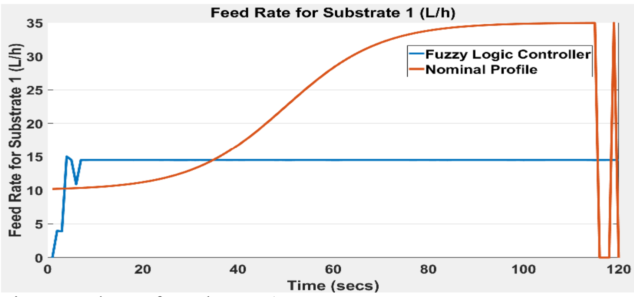


Fig. 7. Feed Rate for Substrate 1

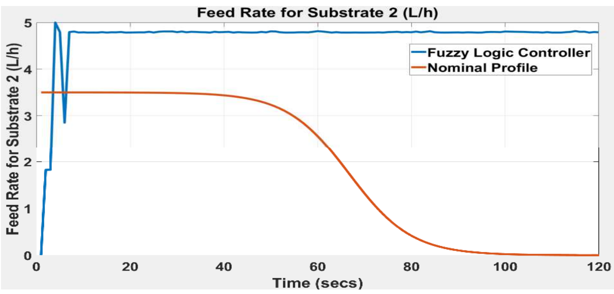


Fig. 8. Feed Rate for Substrate 2

Fig. 7 illustrates that the feed rate of the nominal profile climbs slowly and exhibits unstable behavior near the conclusion of the batch duration. The FLC feed rate, on the other hand, climbs faster than the nominal profile and remains constant at a given level. Similarly, in Fig. 8, the nominal profile's feed rate begins steadily and then dips halfway through the batch period. However, the feed rate from the FLC increases and then stabilizes at a particular level. This demonstrates that the FLC output is controlled and regulated in terms of both input rates (U1 and U2).

The FBF plant's inputs are the feed rates U1 and U2. The plant produces five (5) outputs: biomass, substrate 1, substrate 2, product concentration, and volume, denoted by the letters x, s1, s2, p, and v, respectively. Fig. 9 depicts the product concentration as determined by the nominal profile and the FLC.

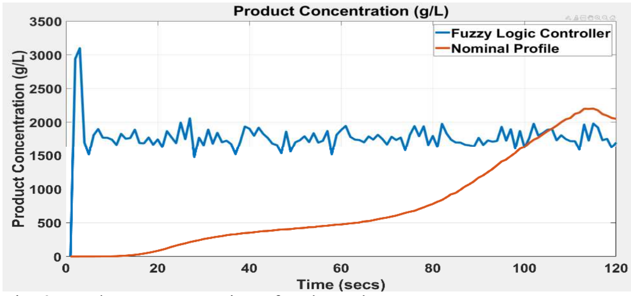


Fig. 9. Product Concentration of Fed Batch Process

Fig. 9 shows that the nominal profile results in a product concentration that steadily increases as the batch duration increases. The FLC, on the other hand, offers product concentration readings that are in accordance with the selected setpoint. The FLC seeks to maintain the controlled variable (in this example, product concentration) constant while minimizing errors. The roughness of the graph is due to the plant's nonlinearity, unpredictability, and complexity. The same inputs delivered into the plant will not create the same output, making obtaining a straight graph or constant output values very challenging. Despite this constraint, the FLC's average product concentration is higher than that of the nominal profile.

The volume of the FBF process is depicted in Fig. 10. The volume calculated from the FLC was compared to the volume calculated from the nominal profile. It can be seen that the volume derived from the FLC is similarly constant along a particular value, as opposed to the nominal profile, which progressively rises. It can also be seen here that, despite the fact that the volume from the FLC is not a controlled variable, it remains stable and rather consistent. To minimize a loss in production, the control scheme keeps volume levels modest.

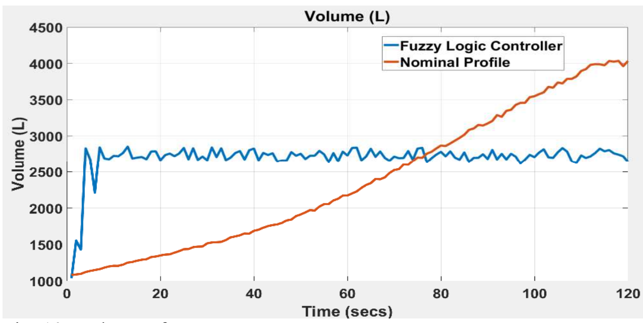


Fig. 10. Volume of FBF Process

Fig. 11 compares the biomass produced by the FBF method to the nominal profile. The biomass derived by the FLC is also consistent, as opposed to the nominal profile, which grows progressively as the batch duration increases. However, the biomass obtained from the nominal profile is much higher than that produced from the FLC in this case.

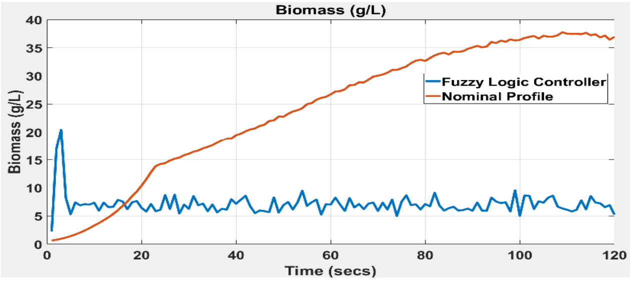

Fig. 11. Biomass of FBF Process

Fig. 12 depicts the productivity graph. The formula in Equation 3 is used to calculate productivity. The graph shows that the FLC has a greater average productivity than the nominal profile.

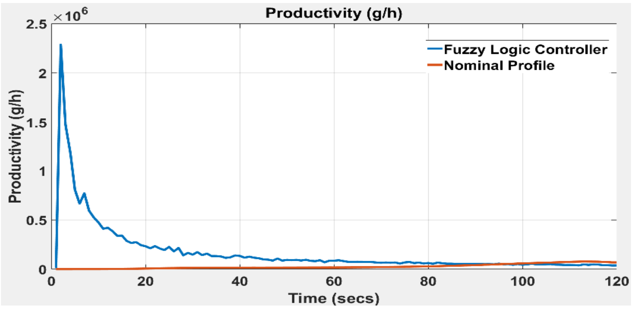

Fig. 12. Productivity of FBF Process

Table III provides a summary of the data collected, including average values for both the FLC and nominal profiles. The data collected is the average of ten (10) simulation runs with a batch time of 120 seconds.

TABLE III. SUMMARY OF FBF RESULTS

| **Value** | $P_{av}$ | $V_{av}$ | $X_{av}$ | $U1_{av}$ | $U2_{av}$ | $J_{av}$ |
|---|---|---|---|---|---|---|
| **Nominal Profile** | 748.93 | 2.37 $x10^3$ | 24.30 | 23.51 | 1.93 | 2.73 $x10^4$ |
| **FLC** | 1.77 $x10^3$ | 2.71 $x10^3$ | 7.20 | 14.20 | 4.70 | 1.74 $x10^5$ |

Table III shows that the FLC provides a much greater product concentration than the nominal profile. The FLC also increases productivity and slightly increases volume. The FLC, on the other hand, results in a large reduction in Biomass. When it comes to feed rates, the FLC provides a lower average feed rate for U1 and a greater feed rate for U2. This demonstrates that the FLC will provide a larger output than the nominal profile with lower feed rates for substrate 1 and somewhat higher feed rates for substrate 2.

## V. CONCLUSION

In MATLAB, the Fuzzy Logic Controller (FLC) was successfully designed and simulated. The resulting findings were compared to the nominal profile using Equations 2 and 3. The FLC resulted in a 137 percent increase in product concentration, a 538 percent improvement in productivity, and a 14 percent increase in volume. The nominal profile, on the other hand, performed better in terms of Biomass, with the FLC providing a 70% decrease in Biomass levels of the fermentation process. The FLC may be used to successfully regulate a FBF process. Future research might seek to overcome the constraint of decreasing biomass by constructing a more robust fuzzy inference system that takes into account more than one parameter.

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