DESIGN OF AN INTELLIGENT FUZZY LOGIC- PID BASED BIOREACTOR CONTROL SYSTEM FOR AN AUTOMATED 50TPD ORGANIC FERTILISER PRODUCTION PLANT WITH AID OF A BM1 ENZYME

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ABSTRACT

Temperature control is crucial for enzyme reactions as changes in temperature can bring a reaction to a complete stop thus killing the enzyme. The greatest challenge on regulating bioreactor conditions is that one has to eliminate percentage overshoot, long rise time and unforeseen transient responds. The main goal of this research was to design a complete control system with aid of hybridized Parallel Structure Fuzzy Logic-PID control algorithm so as to control the enzyme activity in a 50TPD bioreactor for organic fertilizer manufacturing. To achieve this, temperature, pH, pressure and moisture analysis experiments were carried out. Experiments were also done on characterizing the intended raw materials. Process parameters were deduced through modeling and simulation in Matlab and Simulink environments. To a greater extend a process with recommendable rising time; no steady state error and recommendable transient response with no-overshoot was achieved. In comparison with conventional PID controllers the proposed system shows higher control gains when states are away from equilibrium and at the same time retains a lower profile for control signals.

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1 INTRODUCTION

In recent years, fuzzy logic control, mainly fuzzy proportional –integral-derivative controllers have been widely used for industrial applications owing to their heuristic nature associated with simplicity and effectiveness for both linear and non-linear systems [1]. Thus because of the nonlinear property of control gains, fuzzy-PID controllers possess potential to improve and achieve better system performance over the conventional PID controller if the nonlinearity can be suitably utilised.

The paper presents the intelligent control system design of an automated organic fertilizer production plant with an output of 50 tons per day from organic waste with the aid of BM1 enzyme. Section 2 of the paper presents the related literature regarding the design, Section 3 presents the design of the biodigester, Section 4 presents modeling and simulation of the design lastly conclusions and recommendations regarding the design were made.

2 RELATED LITERATURE

This section focuses on the essential theory and critical assessment of the related work needed for the development of the design, it also seeks to present the main arguments and publications by different experts on the subject of automation, fuzzy logic and organic fertilizer production and how it can be used to develop a design which is beneficial and economical.

2.1 Fuzzy Logic Control

In control systems there are a number of generic systems and methods which are encountered in all areas of industry and technology. From the dozens of ways to control any system, it turns out that fuzzy is often the very best way. The only reasons are faster and cheaper. Rajkumar [2] believed that fuzzy logic is a part of artificial intelligence or machine learning which interprets a human's actions. Computers can interpret only true or false values but a human being can reason the degree of truth or degree of falseness. Fuzzy models can interpret the human reasoning and are referred to intelligent systems. Fuzzification is the process of changing a real scalar value into a fuzzy value. This is achieved with the different types of fuzzifiers. Fuzzification of a real-valued variable is done with intuition, experience and analysis of the set of rules and conditions associated with the input data variables.

According to Waznaik [3] fuzzy or multi-valued logic was introduced in the 1930s by Jan Lukasiewicz, a Polish philosopher. While classical logic operates with only two values 1(true) and 0(false), Lukasiewicz introduced logic that extended the range of truth values to all real numbers in the interval between 0 and 1. He used a number in this interval to represent the possibility that a given statement was true or false. Later in 1937, Max Black proposed a concept of "Vagueness; an exercise in logical analysis". In his defence, he argued that a continuum implies degrees. He accepted vagueness as a matter of probability.

The term fuzzy logic is used in two senses:

- *Narrow sense:* Fuzzy logic is a branch of fuzzy set theory, which deals (as logical systems do) with the representation and inference from knowledge. Fuzzy logic, unlike other logical systems, deals with imprecise or uncertain knowledge. In this narrow and perhaps correct sense, fuzzy logic is just one of the branches of fuzzy set theory.
- *Broad Sense:* fuzzy logic synonymously with fuzzy set theory

Wei [1] acknowledged that fuzzy system was first proposed by an American professor, Lotfi A. Zadeh, in 1965 when he presented his seminal paper on "fuzzy sets". Zadeh showed that fuzzy logic unlike classical logic can realize values between false (0) and true (1).Basically, he transformed the crisp set into the continuous set. Zadeh extended the work on possibility theory into a formal system of mathematical logic, and introduced a new concept for applying natural language terms, and he became the "Father" of fuzzy logic. Fuzzy sets thus have movable boundaries. The elements of such sets not only represent true or false values but also represent the degree of truth or degree of falseness for each input.

Fuzzy control systems interpret the expert human and replace them for performing certain control and regulation tasks. Fuzzy controllers apply decision rules (if-then rules) by making use of critical variables to interpolate the output between the crisp boundaries. Cox [4] developed a more realistic ideology which stated that fuzzy logic is not logic that is fuzzy, but logic that is used to describe fuzziness. Fuzzy logic is the theory of fuzzy sets, sets that calibrate vagueness. It is based on the idea that all things admit of degrees. In other words, fuzzy logic is a set of mathematical principles for knowledge representation based on degrees of membership.

Fuzzy logic reflects how people think. It attempts to model our sense of words, our decision making and our common sense. As a result, it is leading to new, more human, intelligent systems. As opposed to the modern control theory, fuzzy logic design is not based on the mathematical model of the process. The controller designed using fuzzy logic implements human reasoning that has been programmed into fuzzy logic language (membership functions, rules and the rule interpretation). It is interesting to note that the success of fuzzy logic control is largely due to the awareness to its many industrial applications.

2.2 Fertiliser processing techniques

The processing of organic fertilizers can be categorized into either anaerobic or aerobic processing.

2.2.1 Anaerobic

In anaerobic decomposition, the breakdown of the organic material is caused by enzymes, bacteria and fungi that thrive in low or no-oxygen conditions. It is the type of decomposition that takes place in closed containers. This type of system is more complex and difficult to control and requires complex equipment for larger scale decomposition of organic matter. Salminen and Rintala [5] stated that advantages of the process are, among others, production of biogas and its use in energy production as well as production of a solid end product which can be used as fertilizer, soil improvement material. Thus Hessami [6] subdivided the process of anaerobic digestion into three separate steps each of which is performed by a different group of microorganisms:

- *Hydrolysis*

In the hydrolysis stage the non-air breathing bacteria, (hydrolytic bacteria) use enzymes to breakdown and liquefy insoluble organic polymers such as carbohydrates, cellulose, proteins and fats. The insoluble organic polymers except proteins are then hydrolyzed to sugars which further decompose to form carbon dioxide, hydrogen, ammonia and organic acids. The latter decomposes to form ammonia, carboxylic acids and carbon dioxide.

- *Acidogenesis*

During this stage the organic acids formed during hydrolysis are converted to acetic acid by acetogenic micro-organisms. At the end of acidogenisis carbon dioxide and hydrogen concentrations start to decrease.

- *Methanogenesis*

The final stage produces 60% Methane and 40% carbon dioxide from the organic acids and other derivatives produced during acidogenesis of the digestion process. The methane is a useful source of fuel and methanogenic bacteria plays a further role in maintaining broad breakdown processes.

Anaerobic disintegration can be very useful to treat arising organic waste such as sewage sludge, organic farm waste, municipal solid wastes, green /botanic wastes, organic and industrial wastes.

2.2.2 Aerobic

In aerobic decomposition, bacteria and fungi which thrive in high oxygen conditions are responsible for the decomposition. This form of decomposition occurs in open organic waste heaps and organic filled containers that allow air to enter. With open heaps and more ventilated containers, organic fertilizer can be formed in a matter of a few months, and even faster if the organic material is turned regularly [5].

2.3 Developed designs and existing systems in organic waste processing

Some of the ideas that have been implemented in organic waste processing include *composting, vermicomposting* and *bio-digestion.* The paper will acknowledge the existence of other waste processing techniques such as composting and vermicomposting however only bio-digestion was considered.

2.3.1 Bio-digestion

Bio-digesters are natural systems that use organic waste, primarily manure, to produce biogas (fuel) and biol (natural fertilizer) by means of anaerobic digestion. Biol is a by-product which consists of a mixture of manure and water that has fermented in the bio-digester. Biol is a liquid fertilizer that can completely replace chemical fertilizer. Biogas as the main product can be used for industrial or domestic purposes to release energy. The process can be wet or dry digestion catalyzed by enzymes or bacteria.

- ***Wet*** – involves dilution of organic matter with a large volume of water.
- ***Dry***–does not involve any dilution with large volume of water. Such systems do not use agitators but may have a slow-speed turner to encourage release of the biogas generated within the mass.

Digestion of manure with other substrates such as food industrial wastes, animal by-products (slaughterhouse waste), or sewage sludge can be highly advantageous which is termed Co-digestion. Acording to Braun and Wellinger [7] some of the benefits include improved balance of total organic carbon, nitrogen, and phosphorous nutrients, which results in a stable and maintainable digestion process and good fertilizer quality.

The typical dairy farm biogas contains approximately 55% to 70% CH_4 and approximately 30% to 45% CO_2. The theoretical CH_4 to CO_2 ratios of various substrates were determined by Jewel [8] using the following equation, developed by McCarty [9]:

$$C_nH_aO_b + \left(n - \frac{a}{4} - \frac{b}{2}\right)H_2O \rightarrow \left(\frac{n}{2} - \frac{a}{8} + \frac{b}{4}\right)CO_2 + \left(\frac{n}{2} + \frac{a}{8} - \frac{b}{4}\right)CH_4 \qquad (1)$$

Readily degradable substrates (urea, fats, and proteins) yield the highest percentages of CH4. However Salminen and Rintala [5], augured that, the fats and proteins available from industrial wastes such as slaughterhouse and rendering operations may, in high concentrations, inhibit the anaerobic digestion process through the accumulation of volatile fatty acids and long chain fatty acids.

2.4 Digester catalyst (Enzyme)

The catalyst can either be a bacteria or an enzyme, however this paper presents a design based on the enzyme although a benchmark was done using a bacteria.

Bacteria are organisms which are single—celled, meaning that they do not have organelles such as a nucleus, where its cells are enclosed in a cell wall which is rigid. They contain all genetic material to reproduce through cellular division. They also show energy-related metabolism and a wide range of nutrient requirements in which some require only minerals and a carbon source such as sugar, while others require more complex growth nutrients. Bacteria play a role in recycling nutrients in the environment during waste digestion. They break down organic matter into simple compounds like carbon dioxide, water, and they cycle important nutrients such as nitrogen, sulfur and phosphorus during the same process. They have a capability of migrating to areas that are rich in specific nutrients for their growth if need be. They are also able to attach themselves to surfaces and form communities. These communities are known as biofilms.

Bacteria can be classified into:

- *Mesophilic anaerobic bacteria*- It means bacteria which can develop in the absence of oxygen and at room temperatures in the range 20°C to 40°C.
- *Thermophilic anaerobic bacteria* - It means bacteria which can develop in the absence of oxygen and at room temperatures in the range 45°C possibly up to 85°C.
- *Heterotrophic anaerobic bacteria* – means bacteria which can assimilate organic carbon-containing sources using oxygen as an energy source which consequently can develop on such sources.

When used in processing of organic waste the type of bacteria used are thermophilic anaerobic bacteria, at a temperature in the range 45°C to 85°C preferably in the range 50°C to 75°C. By use of such a temperature, it eliminates pathogenic germs which include bacteria, yeasts, protozoa, or viruses present if any in the organic waste when it is introduced into a digestion reactor, while allowing the thermophilic bacteria to develop and decompose the organic waste.

According to Stedman's medical dictionary, an enzyme is defined as a macromolecule that acts as a catalyst to induce chemical changes in other substances, while itself remaining apparently unchanged by the process.

BM1 is a white natural blend of healthy bacteria with high heat tolerance capable of acting as powerful enzymes that break down the waste.BM1, which includes keratinase, lipase, cellulose and thermophilic aerobic micro-organisms that accelerates the decomposition and fermentation process, is loaded into a digester along with the waste at a rate of 1 kilogram of BM1 per ton of waste according to Biomax Technologies the manufacturer of the enzyme.BM1 accelerates Thermophilic Digestion Process (TDP). BM1 is able to reduce fermentation time (24 hours or less) by activating fermenting microorganisms at high temperature region (thermophilic process). It is non-genetically modified.

3 DIGESTER INSTRUMENTATION AND PROCESS VARIABLES

Anaerobic processes are still largely dependent upon "manual laboratory analysis" and the adaptation of the system by a "qualified operator." Chromatography, electrochemistry, spectrometric, titrimetric, observers, and some other principles have all been explored as sensing options for anaerobic digestion [10]. In contrast with manual control, where an operator may periodically read the process temperature and adjust the heating or cooling input up or down in such a direction as to drive the temperature to its desired value, in automatic control, measurement and adjustment are made automatically on a continuous basis.

In automatic control a controller compares signal from instrumentation measuring devices with the signal of a process variable, that is desired (set point- The set point is a value for a process variable that is desired to be maintained.) and actuates the final control device. A process variable is a condition that can change the process in some way. In the case of automatic temperature controllers, several types can be used for a given process variable. Achieving satisfactory temperature control, however, depends on;

- The process characteristics

- How much temperature variation from the set point is acceptable and under what conditions (such as start-up, running, idling), and
- Selecting the optimum controller type and tuning it properly.

With digesters, instrumentation measuring devices are used to maintain adequate environmental conditions against possible changes in influent characteristics (temperature level, moisture level, pH, flow rate or composition, reactor pressure) or the conditions inside the reactor. The control of these complex bioprocesses is a difficult task because of the great variety of microorganisms, as well as the long reaction periods [11, 12]. A suitable system to control digesters should maintain the process variables inside the reactor such as temperature, pressure material flow and pH.

3.1 Temperature

Temperature is one of the major important parameters in anaerobic digestion. It determines the rate of anaerobic degradation processes particularly the rates of hydrolysis and methanogenesis. This is a classic measurement, typically with a thermistors or thermocouples. It is a rather important variable for anaerobic digesters where temperature control is often implemented. Moreover, it not only influences the metabolic activities of the microbial population but also has a significant effect on some other factors such as gas transfer rates and settling characteristics of bio solids [13].

3.2 pH

Although pH is a variable that is important in all biological processes, its value is especially critical in anaerobic digestion and nitrification where important quantities of protons are released, eventually leading to acidification and process failure. A low pH value often induces damage in pipes, valves and other metallic components. A measurement of pH at several points in the inlet area is required to ensure efficient plant operation and to monitor the effect of the influent water on the concrete structures and channels. The pH measurement can be done by actual probes. Stronach [13] urged that alkalinity and pH in anaerobic digestion can be adjusted using several chemicals such as sodium (bi-) carbonate, potassium (bi-) carbonate, calcium carbonate (lime), calcium hydroxide (quick lime) and sodium nitrate. The optimal pH values for the acidogenesis and methanogenesis stages are different. During acidogenesis, acetic, lactic and propionic acids are formed and, thus the pH falls. Low pH can inhibit acidogenesis and pH below 6.4 can be toxic for methane forming bacteria (the optimal range for methanogenesis is between 6.6 and 7) an optimal range for all is between 6.4 and 7.2

3.3 Flow rate of fluids

Instruments for the monitoring of gas and liquid flows are ubiquitous in waste treatment. Harremoës *et al* [14] give an extensive overview of liquid flow measurement techniques and point to the importance of proper installation for guaranteed accuracy. For gas flow measurements recurrence is made to Rota meters and, less common, thermal mass flow meters. One of the most important measurements on the entire plant is the accurate measurement of flow at the main pump station inlet. This signal is fed to other parts of the plant as part of the control signal.

3.4 Gases

The Carbon/Nitrogen (C/N) ratio is the relationship between the amount of carbon and nitrogen present in organic materials. For anaerobic digestion an optimum range from 20-30 of C/N ratio is considered to be the best. If the C/N ratio is of high value, it means the nitrogen is consumed rapidly by methanogens for meeting their protein requirements and will not react with the left over carbon content of the material. As a result, this produces very little amount of gas. In a case were the C/N ratio is very low, nitrogen will be released and accumulates in the form of ammonia (NH_4). Ammonia will increase the pH value of the contents in the digester. According to Karki et al. [15] if the pH increases to a pH higher than 8.5, the condition in the digester will start showing toxic effect on methanogen population.

4 DESIGN OF THE FUZZY-PID CONTROL SYSTEM

The design was based on the fact that the pH and the temperature control sub-systems will act as inputs to the proposed bioreactor system. Thus there will be individual controllers fuzzy logic controllers for each parameter (pH and temperature). When the control problem is to regulate the process output around a set-point, it is natural consider error as an input, even to a fuzzy controller, and it follows that the integral of the error and the derivative of the error may be useful inputs as well. In a fuzzified PID controller, however, it is difficult to tell the effect of each gain factor on the rise time, overshoot, and settling time, since it is most often nonlinear and has more tuning gains than a PID controller. Therefore a controller with parallel structure was adopted and the design was derived as follows.

Initially the error and the change of error are defined as;

$$e(k) = r(k) - y(k) \tag{2}$$

$$\Delta e(k) = e(k) - e(k-1) \tag{3}$$

The inputs to the fuzzy are normalised error ($\omega_{e*}e$) and for normalised change in error ($\Delta\omega_{e*}\Delta e$) where $\omega_{e*}$and $\Delta\omega_{e*}$ are weighting factors. Considering the triangular shape there are three inputs of which one is a zero crossing therefore we will consider only the non-zero terms thus *Positive error (P_e)*, *Positive change in error ($P_{\Delta e}$)*,*Negative error (N_e)* and *Negative change in error ($N_{\Delta e}$)*.The corresponding membership functions are defined as follows;

$$\mu_{P_{e1}} = \begin{cases} 0, & \omega_{e1}.e < -1, \\ 1/2 + \frac{1}{2}\omega_{e1}.e, & -1 \le \omega_{e1}.e \le 1, \\ 1 & \omega_{e1}.e \ge 1, \end{cases} \tag{4}$$

$$\mu_{N_{e1}} = \begin{cases} 0, & \omega_{e1}.e < -1, \\ 1/2 + \frac{1}{2}\omega_{e1}.e, & -1 \le \omega_{e1}.e \le 1, \\ 1 & \omega_{e1}.e \ge 1, \end{cases} \tag{5}$$

$$\mu_{P_{\Delta e1}} = \begin{cases} 0, & \omega_{\Delta e1}.\Delta e < 1, \\ 1/2 + \frac{1}{2}\omega_{\Delta e1}.e, & -1 \le \omega_{\Delta e1}.\Delta e \le 1, \\ 1 & \omega_{\Delta e1}.\Delta e \ge 1, \end{cases} \tag{6}$$

$$\mu_{N_{\Delta e1}} = \begin{cases} 0, & \omega_{\Delta e1}.\Delta e < 1, \\ 1/2 + \frac{1}{2}\omega_{\Delta e1}.e, & -1 \le \omega_{\Delta e1}.\Delta e \le 1, \\ 1 & \omega_{\Delta e1}.\Delta e \ge 1, \end{cases} \tag{7}$$

The following membership functions are for the temperature control;

$$\mu_{P_{e2}} = \begin{cases} 0, & \omega_{e2}.e < -1, \\ {}^{1}/_{2} + \frac{1}{2}\omega_{e2}.e, & -1 \le \omega_{e2}.e \le 1, \\ 1 & \omega_{e2}.e \ge 1, \end{cases} \tag{8}$$

$$\mu_{N_{e2}} = \begin{cases} 0, & \omega_{e2}.e < -1, \\ {}^{1}/_{2} + \frac{1}{2}\omega_{e2}.e, & -1 \le \omega_{e2}.e \le 1, \\ 1 & \omega_{e2}.e \ge 1, \end{cases} \tag{9}$$

$$\mu_{P_{\Delta e2}} = \begin{cases} 0, & \omega_{\Delta e2}.\Delta e < 1, \\ {}^{1}/_{2} + \frac{1}{2}\omega_{\Delta e2}.e, & -1 \le \omega_{\Delta e2}.\Delta e \le 1, \\ 1 & \omega_{\Delta e2}.\Delta e \ge 1, \end{cases} \tag{10}$$

$$\mu_{N_{\Delta e2}} = \begin{cases} 0, & \omega_{\Delta e2}.\Delta e < 1, \\ {}^{1}/_{2} + \frac{1}{2}\omega_{\Delta e2}.e, & -1 \le \omega_{\Delta e2}.\Delta e \le 1, \\ 1 & \omega_{\Delta e2}.\Delta e \ge 1, \end{cases} \tag{11}$$

Therefore there are nine rules used for the control system including the zero regions as illustrated in Figure 5. The fuzzy labels of the control outputs are singletons defined as P=1, Z=0 and N=-1.Implementing methods such as Larsen's product inference method with Zadeh fuzzy logic AND Lukasiewcz fuzzy logic OR, using the traditional centre-of-gravity (COG) deffuzification, and for simplicity considering $\omega = \omega_{e1} = \omega_{e2}$ and $\omega = \omega_{\Delta e1} = \omega_{\Delta e2}$, the control output of each FLC can be obtained , in the universe of discourse as follows;

$$u_1^{(F)} = \frac{\omega_{\Delta u1}}{4 - 2max(\omega_{e1}|e|, \omega_{\Delta e1}|e|)}(\omega_{e1}e + \omega_{\Delta e1}\Delta e) = \frac{\omega_{\Delta u}}{4 - 2\alpha}(\omega_e e + \omega_{\Delta e}\Delta e) \tag{12}$$

$$u_2^{(F)} = \frac{\omega_{\Delta u2}}{4 - 2max(\omega_{e2}|e|, \omega_{\Delta e2}|e|)}(\omega_{e2}e + \omega_{\Delta e2}\Delta e) = \frac{\omega_{\Delta u}}{4 - 2\alpha}(\omega_e e + \omega_{\Delta e}\Delta e) \tag{13}$$

Where

$$\propto = 4 - 2max(\omega_{e1}|e|, \omega_{\Delta e1}|e|) = 4 - 2max(\omega_{e2}|e|, \omega_{\Delta e2}|e|) = 4 - 2max(\omega_e|e|, \omega_{\Delta e}|e|) \tag{14}$$

The overall fuzzy control output will be;

$$u_{PID}^{(F)} = \sum_0^k \Delta u_1^{(F)} + u_2^{(F)} \tag{15}$$

Therefore

$$u_{PID}^{(F)} = \sum_0^k \frac{\omega_{\Delta u}\omega_{\Delta e}}{4 - 2\propto}\left(\Delta e + \frac{\Delta t}{{}^{\omega_{\Delta e}}/_{\omega_e}\Delta t}e\right) + \frac{\omega_u\omega_e}{4 - 2\propto}\left(\Delta e + \frac{\Delta t}{{}^{\omega_{\Delta e}}/_{\omega_e}\Delta t}e\right) \tag{16}$$

If we however chose,

$$K_c^{(F)} = \frac{\omega_{\Delta u}\omega_{\Delta e}}{4 - 2\propto} \tag{17}$$

$$T_i^{(F)} = \frac{\omega_{\Delta e}}{\omega_e}\Delta t \tag{18}$$

$$K_c^{(F)}\frac{T_d^{(F)}}{T_i^{(F)}} = \frac{\omega_u\omega_e}{4 - 2\propto} \tag{19}$$

Then the fuzzy control output derived from the above equations can be combined in a fuzzy-PID as follows;

$$u_{PID}^{(F)} = \sum_0^k K_c^{(F)} \left(\Delta e + \frac{\Delta t}{T_i^{(F)}} e \right) + K_c^{(F)} \frac{T_d^{(F)}}{T_i^{(F)}} \left(e + T_i^{(F)} \frac{\Delta e}{\Delta t} \right) \tag{20}$$

Considering the fact that the constants of the bioreactor plant are sufficiently large compared with sampling interval, which is common and reasonable in process control, such that;

$$\dot{e} \approx \frac{\Delta e}{\Delta t} \tag{21}$$

Therefore the overall control output can be approximated as;

$$u_{PID}^{(F)} = \int_0^{k.\Delta t} K_c^{(F)} \left(de + \frac{e}{T_i^{(F)}} dt \right) + K_c^{(F)} \frac{T_d^{(F)}}{T_i^{(F)}} \left(+ T_i^{(F)} \frac{de}{dt} \right) \tag{22}$$

$$u_{PID}^{(F)} = \int_0^{k.\Delta t} K_c^{(F)} \dot{e} dt + \int_0^{k.\Delta t} \frac{K_c^{(F)}}{T_i^{(F)}} e dt + \frac{K_c^{(F)} T_d^{(F)}}{T_i^{(F)}} \left(e + T_i^{(F)} \dot{e} \right) \tag{23}$$

Thus equation (23) represents the fuzzy-PID for a parallel fuzzy control system.

The designed Simulink model was as shown in Figure 1.0 below. The main goal was to achieve a cascaded system for the PID Controller and the Fuzzy Controller, with the output crisp value of the Fuzzy controller being an input to the PID controller.

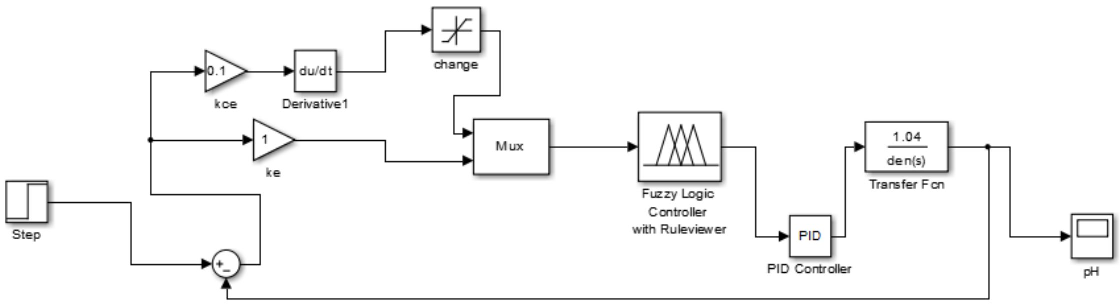

Figure 1: The proposed Simulink Fuzzy-PID Model

The design reflected challenges on the system Transfer Function, after testing several values and tuning the final system transfer function was as shown in equation (24).

$$G_{(s)} = \frac{1.04}{0.2s^2 + 1.5s + 1} \tag{24}$$

4.1 Development of the fuzzy controller

Fuzzy inference can be defined as a process of mapping from a given input to an output, using the theory of fuzzy sets. The most commonly used fuzzy inference technique is the so-called Mamdani method. In 1975, Professor Ebrahim Mamdani of London University built one of the first fuzzy systems to control a steam engine and boiler combination [16]. He applied a set of fuzzy rules supplied by experienced human operators. The Mamdani-style fuzzy inference process is performed in four steps: fuzzification of the input variables, rule evaluation, aggregation of the rule outputs, and finally defuzzification.

4.1.1 Fuzzification

The first step is to take the crisp inputs, x_1 (error) and x_2 (error change), and determine the degree to which these inputs belong to each of the appropriate fuzzy sets. The crisp input is always a numerical value limited to the universe of discourse. In our case, values of x_1 and x_2 are limited to the universe of discourses X_1 and X_2, respectively. The ranges of the universe of discourses were determined by expert judgements. Once the crisp inputs, x_1 and x_2, are obtained, they are fuzzified against the appropriate linguistic fuzzy sets.

4.1.2 Rule evaluation

The second step was to take the fuzzified inputs, and apply them to the antecedents of the fuzzy rules. If a given fuzzy rule has multiple antecedents, the fuzzy operator (AND or OR) is used to obtain a single number that represents the result of the antecedent evaluation. This number (the truth value) is then applied to the consequent membership function. To evaluate the disjunction of the rule antecedents, we use the OR fuzzy operation. Typically, fuzzy expert systems make use of the classical fuzzy operation union. The rules were developed and the correlations between inputs were derived as shown in Figure 2. A linguistic variable carries with it the concept of fuzzy set qualifiers, called hedges. Hedges are terms that modify the shape of fuzzy sets. They include adverbs such as very, somewhat, quite, more or less and slightly. Hedges can modify verbs, adjectives, adverbs or even whole sentences.

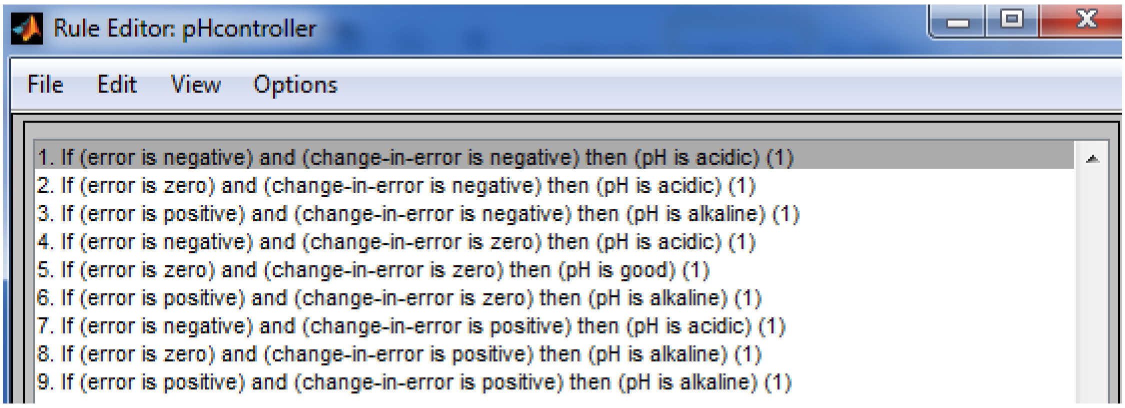

Figure 2: The proposed Simulink Fuzzy-PID Model

4.1.3 Aggregation of the rule outputs

Aggregation is the process of unification of the outputs of all rules. In other words, we take the membership functions of all rule consequents previously clipped or scaled and combine them into a single fuzzy set. Thus, the input of the aggregation process is the list of clipped or scaled consequent membership functions, and the output is one fuzzy set for each output variable.

4.1.4 Defuzzification

The last step in the fuzzy inference process is defuzzification. Fuzziness helps us to evaluate the rules, but the final output of a fuzzy system has to be a crisp number. The input for the defuzzification process is the aggregate output fuzzy set and the output is a single number. There are several defuzzification methods as stated by Cox [4], but probably the most popular one is the centroid technique. It finds the point where a vertical line would slice the aggregate set into two equal masses.

5 SIMULATION RESULTS

To achieve the set objective the system was initially tested without a fuzzy controller so as to justify the need for the fuzzy controller in cascade with the PID controller and the results were displayed as shown in Figure 3.

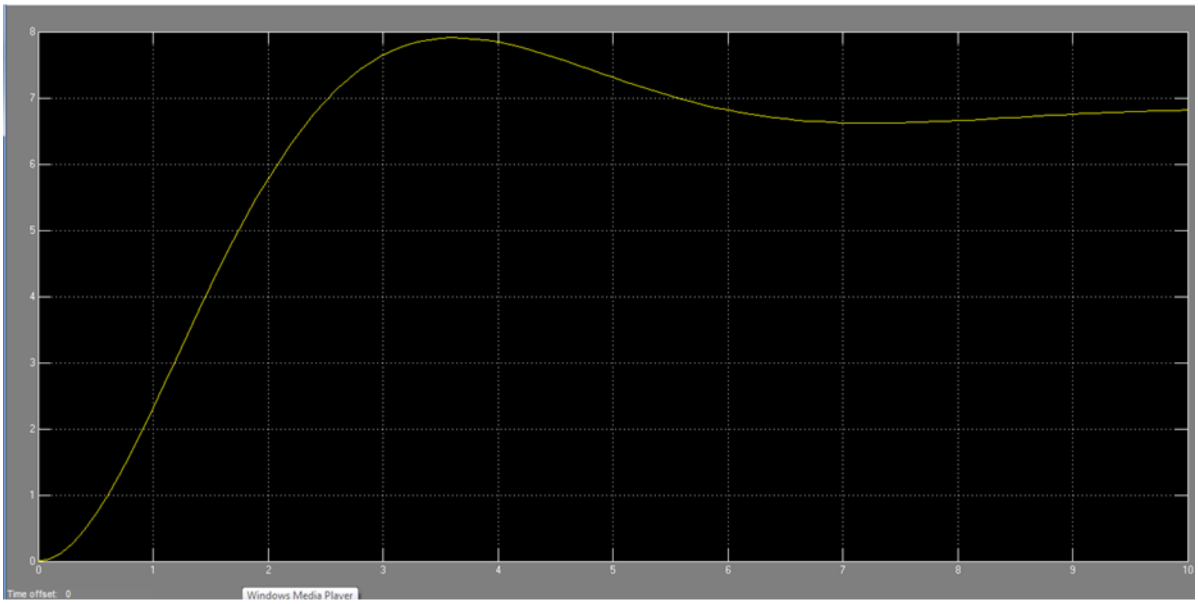

Figure 3: The system output for a PID Model

The motive for this research was to develop a system which will be able to operate without any percentage overshoots above the recommended range of 6.6≤pH<7.0; the results shown in Figure 3 were not favourable for the operation of the enzyme. The enzyme requires an acidic environment and any deviation towards the alkaline environment will result in sudden death of the active enzyme. Although the results in Figure 3 shows a system operating in acidic condition, the fact that the system has an overshoot close to pH=8 reveals that the bulk of the enzyme would have been destroyed between the 2sec≤t(s)≤7sec. This has motivated the inclusion of a Fuzzy controller which has the capability to reason with imprecise or partial data, the results are shown in Figure 4.

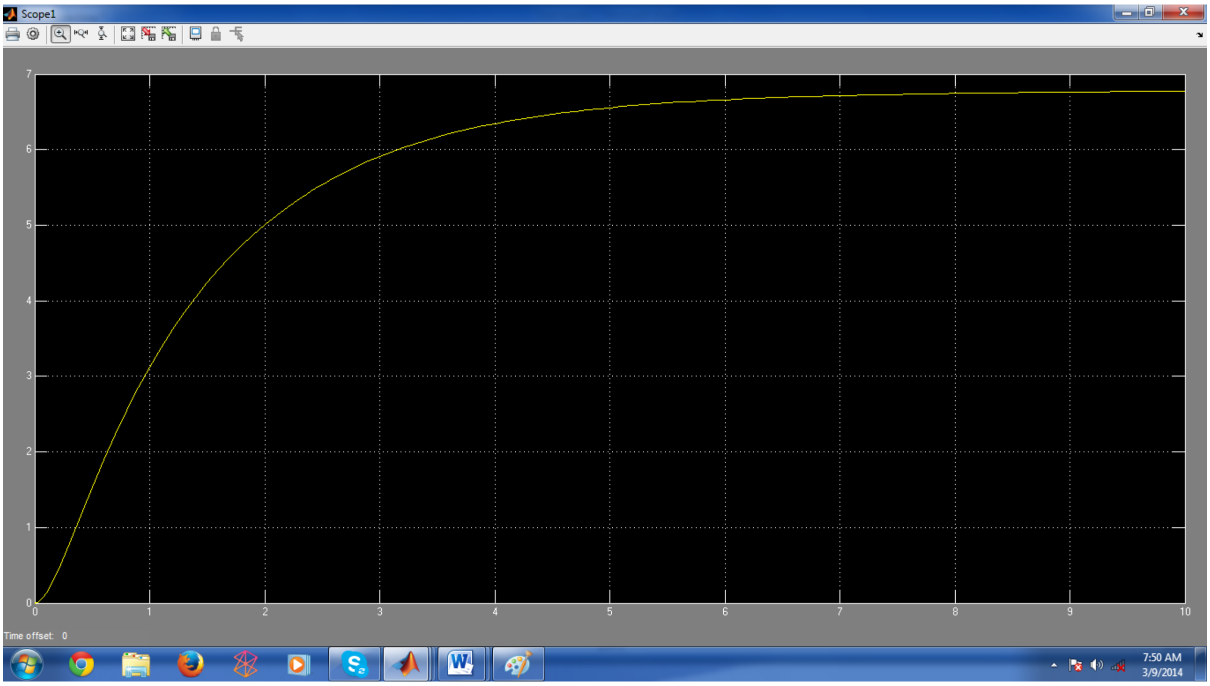

Figure 4: The system output for a Fuzzy-PID Model

The final results revealed that the design is achievable with no percentage overshoot. There was need to have a trade-off between having a short rise time and achieving a system with no percentage overshoot. The fuzzy logic result illustrated in Figure 5 below, shows that the system has an average output of pH=6.8 under wide range of variable system disturbances.

The optimum operating range for the BioMax1 enzyme is between 6.6 and 7.0 thus the stable value of 6.8 is acceptable for optimum enzyme performance.

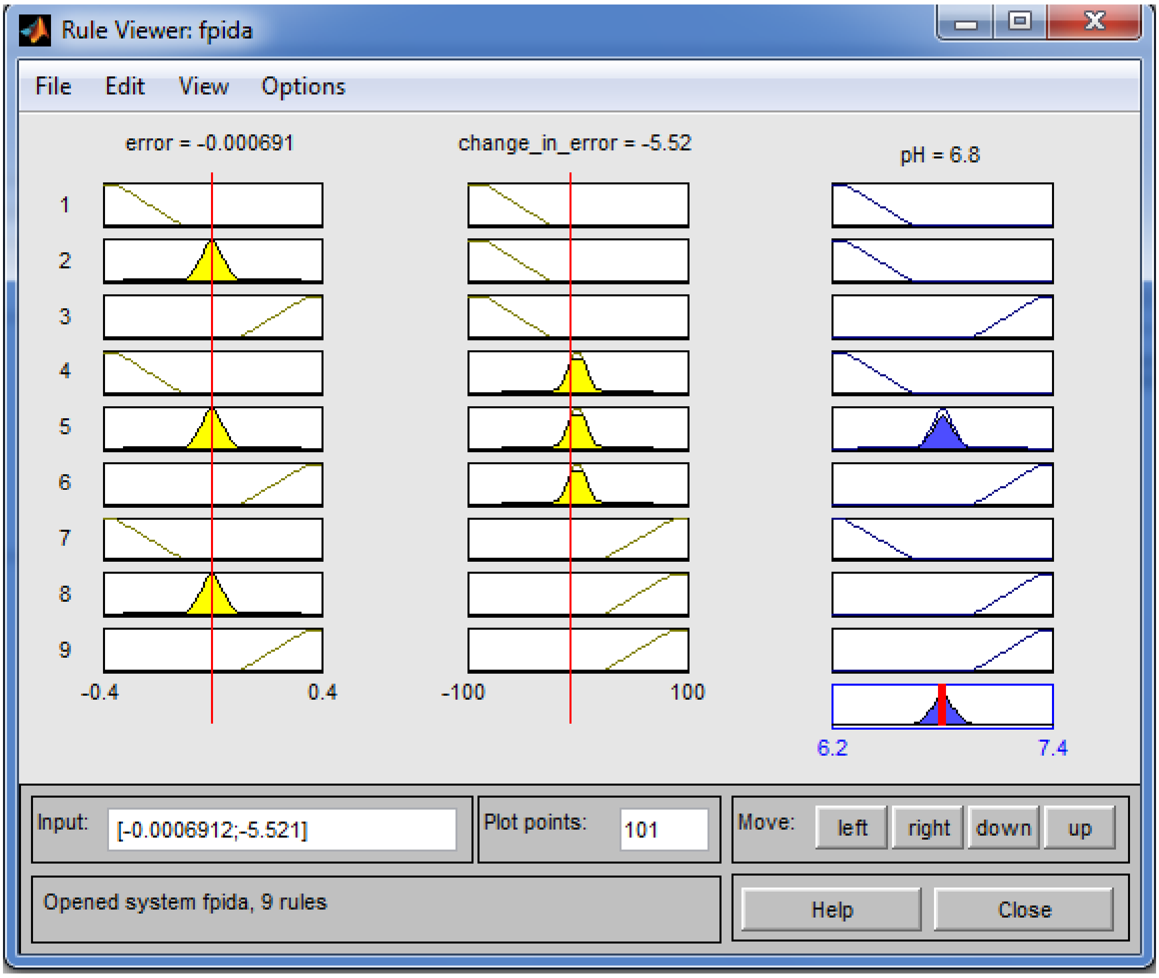

Figure 5: The system Fuzzy-PID rules

6 CONCLUSION

In a nutshell the main objective of this project was to come up with a suitable controller which is capable of minimizing overshoots, reduce rise time and transient response under non-linear conditions. The set objective was achieved. A sensitivity of the fuzzy logic controller to design parameters, different shapes and superposition of membership functions was tested. It was also concluded that since fuzzy logic is determined as a set of mathematical principles for knowledge representation based on degrees of membership rather than on crisp membership of classical binary logic if used in cascade with a PID controller complex systems can easily be modeled without the aid of mathematical modeling.

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