Artificial Intelligent Control Techniques for Nonlinear Real Time Chemical Reactor

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***Abstract*—Biodiesel, an alternative diesel fuel made from a renewable source, is produced by the transesterification of vegetable oil or fat with methanol or ethanol. In order to control and monitor the progress of this chemical reaction with complex and highly nonlinear dynamics, the controller must be able to overcome the challenges due to the difficulty in obtaining a mathematical model, as there are many uncertain factors and disturbances during the actual operation of biodiesel reactors. This paper proposes controllers, namely artificial intelligent controllers; online iterative learning controller updating the fuzzy logic controller, inverse adaptive neuro-fuzzy inference system controller and Genetic Algorithm (GA) with ANFIS model is used for PID parameter tuning. These are used as real-time control system for industrial microwave reactor to produce biodiesel from waste cooking oil and animal's fats. The controllers are used to automatically and continuously adjust the applied power supplied to the microwave reactor under different perturbations. A LabVIEW based software tool is used for measurement and control of the full system, with real time monitoring.**

Keywords-ANFIS; FLC; ILC;GA; LabVIEW.

I. Introduction

A. Production of Biodiesel from Waste Oil

Biodiesel, a derivative from plant oils or animal fats, has gained widespread acceptance in recent years as a sustainable alternative fuel to petroleum diesel due to its environmental benefits, renewability, its non-toxicity and biodegradable characteristics [1]. With increasing world crude oil prices, the focus of research is to produce biodiesel fuels from very poor quality, waste cooking oil [2]. Oils are generally poured down the drain, resulting in problems for waste water treatment plants and energy loss [3].

According to the first UK Renewable Fuels Agency report on fuels supplied under the Renewable Transport Fuels Obligation for April to May 2008, biofuels accounted for 2.14% of all UK road fuel with biodiesel achieving 3.43% of the diesel market and bioethanol 0.6% of the gasoline market [4]. The majority of biodiesel sold in the UK was imported, with 50% of the total amount coming from an unknown origin and 16% of the total being sourced from unknown feedstocks. The current blended-limit for forecourt biodiesel in the UK is 5% though levels up to 30% are possible while still complying with the fuel standard EN 590.

Although there are several different ways in which biodiesel can be used or formulated as a fuel such as direct blending, microemulsions and thermal cracking, the most widespread remains the alkyl esters of fatty acids obtained through transesterification of the oils or fats [5]. In transesterifcation triglycerides which are the main chemical in oils or fats are converted into esters through reaction with simple alcohols. The physical and chemical properties of the esters obtained by this process are very similar to those of the petroleum diesel. Fig. 1 shows the schematics of biodiesel production from waste cooking oil.

The quality of the biodiesel produced is closely related to the performance of the biodiesel reactors, and their proper control poses a number of challenges. These arise from the presence of multiple chemical reactions, the complex heat and mass transfer characteristics [6], as well as from nonlinearities due to fluctuations of reactant concentration, reactant temperature, coolant temperature, ambient temperature, instrumentation noise, or miss-calibration [7]. The control design of the biodiesel reaction is different from plant to plant and basically depends on the production technology adopted [8].

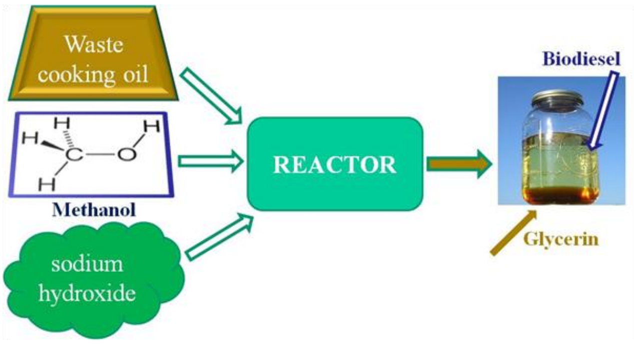


Figure 1. Schematics of biodiesel production from waste cooking oil.

B. Use of Fuzzy Controllers

Fuzzy controllers have been widely used in industrial control due to their capability to deal with highly non-linear and ill-defined systems [9], and are based upon a number of very important fuzzy rules describing the reaction of the real time system under control [10]. These rules are based on experience, operator's control action and a fuzzy model of the plant [11].

Classical controllers show significant difficulties when trying to control the system automatically. Controllers can be: artificial intelligent controllers (Fuzzy logic controller (FLC), online Iterative learning controllers (ILC) updating the Fuzzy logic controller and inverse Adaptive Neuro-Fuzzy Inference System (ANFIS) controller. FLC can incorporate expert human judgment to define the system variables and their relationships which cannot be defined by mathematical relationships. FLC has to be tuned to deliver the desired response by online updating the membership functions (MFs) using Iterative Learning Control (ILC). And inverse ANFIS controller consists of components of a fuzzy system except that computations at each stage are performed by a layer of hidden neurons and the neural network's learning capability is provided to enhance the system knowledge.

Therefore, the design of these controllers requires the construction of a decision table and MFs, which increase with system complexity and number of controller inputs. Efficient and low complexity controller is designed using self-updating FLC by utilizing membership function modification. Complexity of the controller has been reduced with an overall improvement in performance, particularly in difficult operating conditions. This controller was compared with conventional FLC and inverse ANFIS controller to evaluate the robustness of this controller under online nonlinear real time chemical system application.

Logic rules and membership functions are two key components of a FLC [12]. The challenging task associated with FLC design has always been to choose appropriate MFs and minimum rule base. For this reason FLC has to be tuned to deliver the desired response. Many techniques have been applied including neural networks and type2 fuzzy [13]. So far these methods are complex and difficult in implementation, although ILC with FLC as self tuning FLC or self learning FLC was considered [14], most of them in theoretical research.

II. Novel Approach to Biodiesel Reactor Control

However, the approach followed here is based on the tuning parameters of standard FLC by adding online gradient adaptation factor with width adaptation of membership function using ILC at each time instant according to the error between the setpoint and output temperatures. This technique gives the hybrid controller more range to change in MFs with respect to the real time error and gives the advantages to reduce the number of MFs and the logic rules.

In this work the hybrid controller reduced the MFs from 5 MFs for each control input and 7 MFs in output, to only 3 MFs (for each error, change of error and the output), and reduced the rules from 25 rules to 9 rules only. Another novel approach design is PID ccontroller updated genetically by using ANFIS model for microwave biodiesel reactor.

There are a number of ways to produce heating to assist biodiesel production, for example, splate heater, muffle furnace or microwave oven [15] In this work a microwave system has been used as a heating source [16] for the reactor to produce biodiesel from waste cooking oil and animal fats. Microwaves at a frequency of 2.45 GHz were used to reduce the chemical reaction time, from hours under conventional heating, to minutes for the same volume of waste input. This novel microwave reactor is capable of operating at commercial production rates (kg/hr) instead of laboratory scale (g/day). All the changes in the control system could be observed in real time and user commands could be accepted during the process. Developed biodiesel system is shown in Fig. 2.

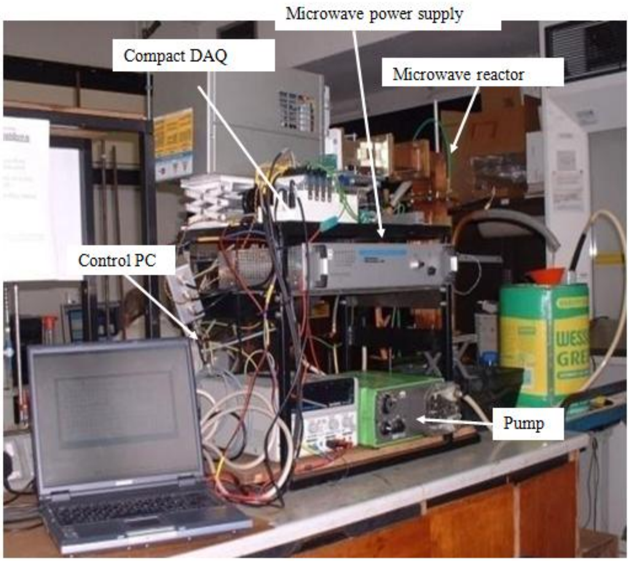


Figure 2. Developed biodiesel system.

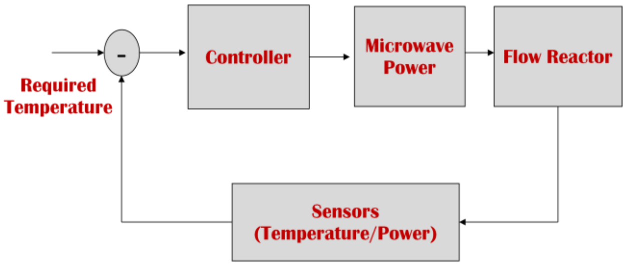


Figure 3.Block-diagram of the process, where microwave power supplied to flow reactor is regulated by a controller via temperature/power sensors of feedback loop.

Automated the monitored and controlled system was developed using laptop computer and National Instrument's Data Acquisition (DAQ) with LabVIEW software interface.

LabVIEW stands for **Lab**oratory **V**irtual **I**nstrument **E**ngineering **W**orkbench, and is a graphical programming language which was used to receive the signals from the transducers through the DAQ, to process the signals and send the output signals to the controlled equipment. All the changes in the control system could be observed in real time and user commands could be accepted during the process, as shown in Fig. 4.

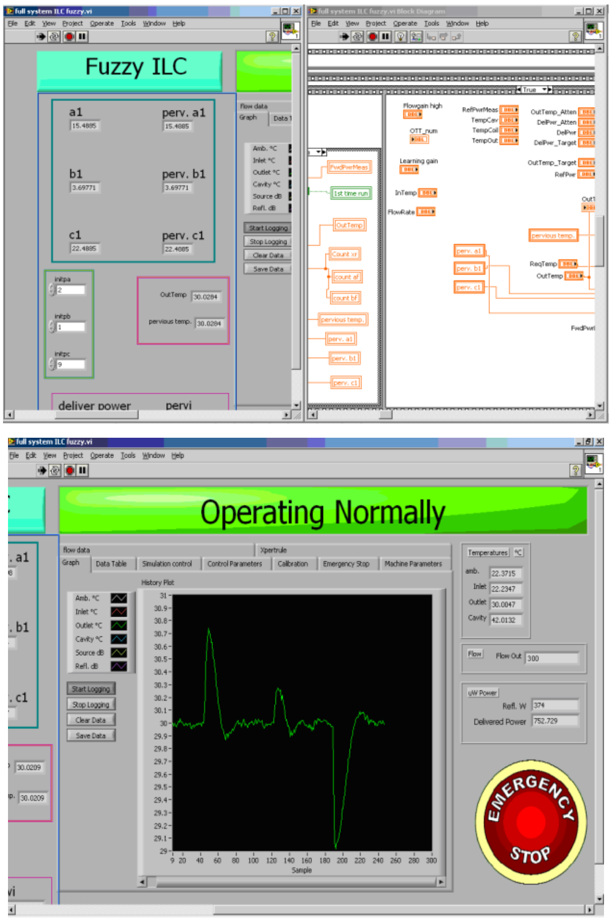


Figure 4. LabView control of the biodiesel reactor operation.

III. CONTROLLERS DESIGN

A. Standard Fuzzy logic controller (FLC)

Many of chemical reactions are sensitive to temperature, and temperature control has a key role in most chemical processes [17]. In addition, precision and quality control of temperature (with minimum overshoots and undershoots, fast rise and settling times) is desirable [18, 19]. Interestingly, craziness based particle swarm optimization (CRPSO) is claimed [19] to be moderately fast algorithm that yields true optimal gains and minimum overshoot, minimum undershoot and minimum settling time of the transient response for any system, also the feasibility of this approach is yet to be tested.

Classical control theory usually requires a mathematical model for designing the controller [20]. In order to control and monitor the progress of the chemical reaction with complex and highly nonlinear dynamics in biodiesel chemical reaction, the controller must be able to overcome the challenges due to the difficulty in obtaining a mathematical model. Inaccurate mathematical modeling of the plants usually degrades the performance of the controller, especially for nonlinear and complex control problems [21]. Hence the process needs an alternative control mechanism that assures precision and quality control for even non linear and time varying systems. FLC offers an advantage over traditional adaptive control systems, as this alternative control mechanism assures precision and quality for even non-linear and time varying systems [22]. Fuzzy control which is based on human expert decision making do not require mathematical model of the plants.

A Fuzzy controller is composed of three calculation steps [23] as shown in Fig. 5. First step, fuzzification, is a function of accepting input values and determining the degree of membership to some pre-selected linguistic terms. Fuzzy Inference consists of determining the relationships based upon If-Then rules used to obtain more weighted outputs. These outputs are also linguistic variables in nature and have a nonlinear relationship. Defuzzification involves converting the output term into a crisp value such that it is compatible with the system.

The Fuzzy controller was based on the Mamdani Fuzzy logic Labview Toolkit. The first Fuzzy input represents the error between the measured temperature and the setpoint. The second Fuzzy input represents the change in error. Fig. 6 shows the membership functions, (a) for the error and (b) for the change of error over the range of input variable values and linguistically describes the variables universe of discourse. Five membership functions were selected with triangle shape as follows: large positive, small positive, zero, small negative, large negative. The universe of discourse for the error and the change of error were -18 to 18 and -12 to 12 respectively. The left and right half of the triangle membership functions for each linguistic label was chosen to provide a membership overlap with adjacent MFs.

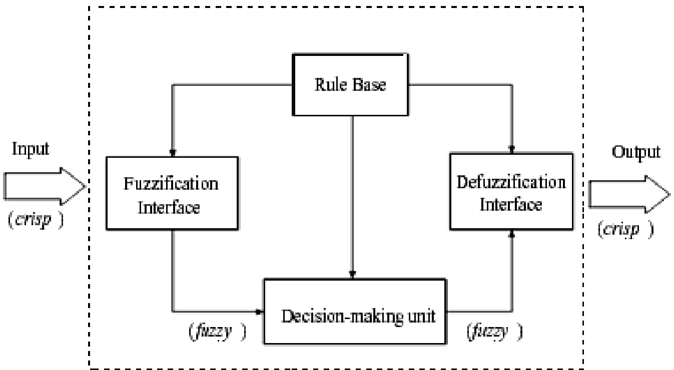


Figure 5. Basic block diagram for a fuzzy controller [3].

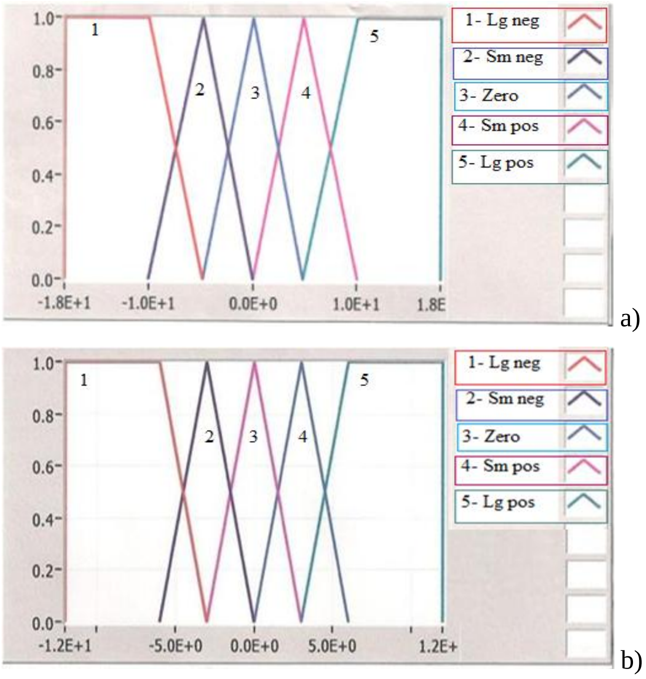


Figure 6. Fuzzy inputs membership functions (a) error, (b) change of error.

Fuzzy logic controller output is the delivered power which is applied to microwave reactor. Output variable is chosen to interval from -100 to 100 with seven triangle membership functions; large positive, medium positive, small positive, zero, small negative, medium negative, large negative. The rule base of the fuzzy controller gives the decision that in which of the five MFs have to fire. Rule evaluation part has 25 fuzzy rules as shown in Fig. 7. Table 1 shows the fuzzy logic control rules developed for the proposed system. Note that *e* denotes the overall online system error, according to (1):

$$e = T_{set} - T_{out} \quad (1)$$

where T_{Set} is the desired output temperature and T_{out} is the actual plant output temperature.

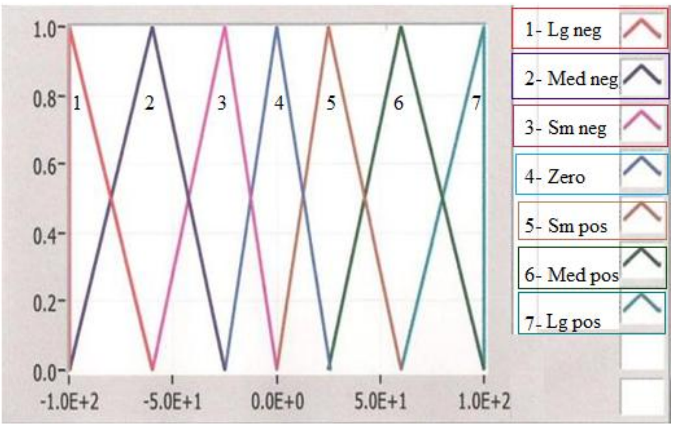


Figure 7. Membership functions of the output linguistic variables.

TABLE I. FUSSY RULES FOR BIODIESEL SYSTEM

Δe \ e	Lg neg	Sm neg	Zero	Sm pos	Lg pos
Lg neg	Lg neg	Med neg	Med pos	Med neg	Sm pos
Sm neg	Med neg	Sm neg	Sm pos	Zero	Sm pos
Zero	Sm neg	Sm neg	Zero	Sm pos	Sm pos
Sm pos	Sm neg	Zero	Zero	Sm pos	Med pos
Lg pos	Sm neg	Sm pos	Zero	Med pos	Lg pos

B. *Iterative Learning Controller Design*

There are many desirable features that make ILC an attractive control strategy in solving real-time control problems [24], such as simple structure, control quality and reliability, it can fully use process information such as the past tracking error and past control signal over the entire operation, it is a memory based learning mechanism and memory devices are cheap with the present microprocessor technology, ability to achieve a perfect tracking both in the transient period and steady state with repeated learning, almost model-free nature in design and real-time execution, unlike many control methods that require system model knowledge [25] and ILC is the availability of non-causal signals for control compensation. ILC aim is to improve the transient control performance along the time domain.

However, ILC has a poor response in the iteration domain. This disadvantage and the complexity of fuzzy controller can be mitigated by combining these two controllers into a single so called hybrid controller.

The proposed controller is designed by integrating MATlab into LabVIEW successfully. First hybrid controller (FLC with ILC) input represents the error between measured temperature and setpoint. The second fuzzy input represents the change in error. The general block diagram of the hybrid controller is shown in Fig. 8.

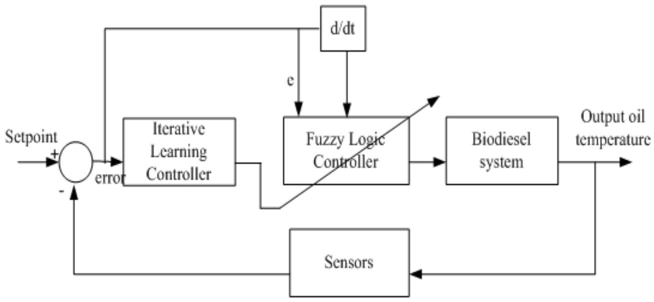


Figure 8. Self-learning Fuzzy Logic controller using ILC.

Three reduced MFs are selected with triangle shape as follows: positive, zero and negative for the inputs variable: error (e) and change in error (Δe); and for output variable: delivered power which is applied to microwave reactor (P) as shown in Fig. 9. The universe of discourse for the error and change of error are from -30 to 30 and -12 to 12 respectively. The interval of output variable is chosen to be from -100 to

100. In this case, rule evaluation part has 9 reduced fuzzy rules.

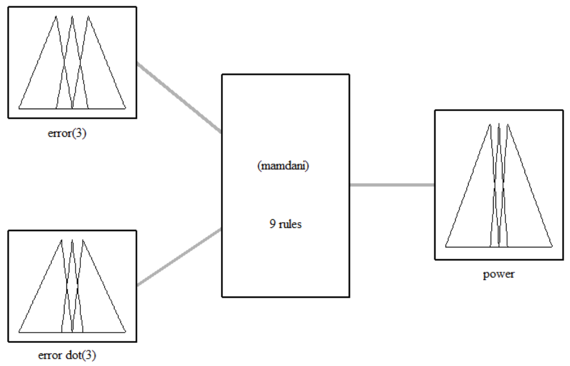


Figure 9. Integrating MATlab into LabVIEW for biodiesel system: 2 inputs, 1 output, 9 rules.

Table 2 presents the self-learning fuzzy logic control rules. The proposed tuning algorithm is illustrated in Fig. 10. The end points of zero range for linguistic variable (e, Δe, P) are labeled ($-M_k$, M_k). These points are also representing the centers for negative and positive ranges of triangular MFs for linguistic variable (e, Δe, P). Due to the symmetry of MFs, one learning control law is needed for each variable. The location of point M is updated along the linguistic variable; depends on tracking online system error. The modifications for all MFs are by changes in the width of zero range and slops for positive and negative ranges.

TABLE II. SELF-LEARNING FUSSY RULES FOR BIODIESEL SYSTEM

Δe \ e	Neg	Zero	Pos
Neg	Neg	Zero	pos
Zero	Neg	Zero	pos
Pos	Neg	Zero	Pos

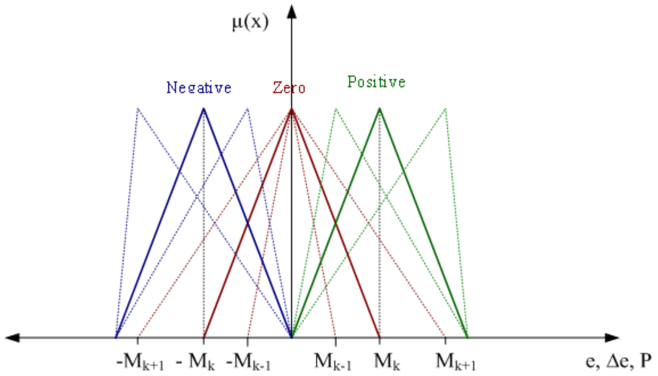


Figure 10. Triangular MFs modification according to the ILC law.

The end points of zero range for linguistic variable (e, Δe, P) are labeled (-Mk, Mk). These points are also representing the centers for negative and positive ranges of triangular MFs for linguistic variable (e, Δe, P). Due to the symmetry of MFs, one learning control law is needed for each variable, according to (2). The location of point M is updated along the linguistic variable; depend on tracking online system error. Due to this updating, the modifications have been happened for all MFs by changes the width of zero range and slops for positive and negative ranges.

$$M_{\kappa+1}=M_{\kappa}+\phi e \tag{2}$$

where *M* is the modification point for each linguistic variable (e, Δe, P), k is the current iteration and ϕ is the learning step.

The proposed controller is stable and converges due to the following reasons:

a) the desired output signal is repeatable over a finite time interval;

b) the system is stable under FLC without ILC;

c) the control input signal is bounded;

d) the universe of discourse for the error, change of error and deliver power is not modified, and is chosen according to experts of the plant to ensure the stability of the system;

e) the modifications of MFs give a good width for zero MF in small value of error to minimize steady state error with symmetry in positive and negative triangular shape for MFs in large value of error;

f) there are three learning steps ((ϕ_e, $\phi_{\Delta e}$, ϕ_P)) for each linguistic variable (e, Δe, P) respectively, and they are chosen to ensure good tracking performance even in the presence of uncertainty so that $T_{out} \rightarrow$Setpoint as $k\rightarrow\infty$.

Fig. 11 illustrated the modification steps of MFs for error in 300 ml/min flow rate: (a) at inlet temperature, (b) at 30 °C setpoint, (c) at 35 °C.

C. *Adaptive Neuro- Fuzzy Inference System control*

Within the multitude of adaptive control schemes, the self-tuning approach has received considerable attention [7, 26] along with the proportional-integral-derivative (PID) control algorithms [27]. PID controllers have been used in most of the feedback loops of process industries despite continual advances in control theory. These controllers are preferred because of their versatility, simple structure, high reliability and easy implementation on analog or digital platforms. Nowadays, around 90% of industrial objects are controlled by PID controllers [28].

Fuzzy logic controllers are fuzzy rule-based systems comprising expert knowledge in form of linguistic rules. These rules are usually constructed by an expert in the field of interest who can link the facts with the conclusions. However, this way to work sometimes fails to obtain an optimal behavior [29]. An intelligent control system is expected to possess inbuilt adaptation/learning and decision-making capability so that it is able to meet desired performance over a very wide range of uncertainty. To overcome the limitations of traditional computing paradigm, the researchers are searching for new computational approaches that can be used to model, partially, the functioning of neural system and can be used to solve real world problems efficiently [30]. One of these intelligent methods is artificial fuzzy method.

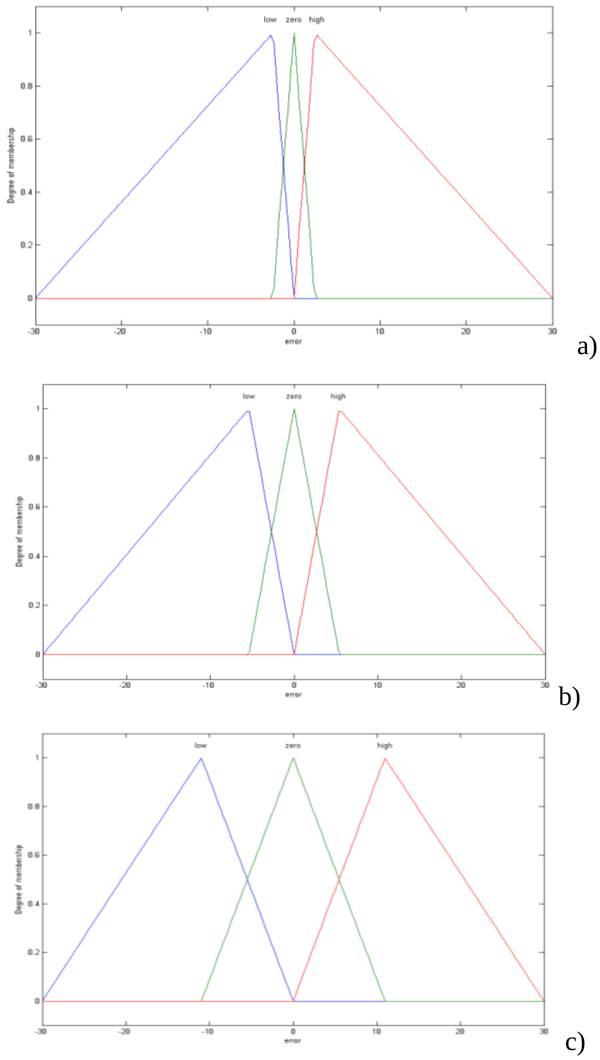


Figure 11. Modification steps of MFs for error in 300ml/min flow rate: (a) at inlet temperature, (b) at 30 °C setpoint, (c) at 35 °C.

There are many advantages of fuzziness, one of which is the ability to handle blur data. Fuzzy methods provide linguistic labels for complex system modeling [31, 32]. Adaptive Neuro fuzzy Inference System (ANFIS) is an intelligent control technology, provides a systematic method to incorporate human experience and implement nonlinear algorithms, characterized by a series of linguistic statements, into the controller [33].

ANFIS is widely used in complex system studies for modeling, control or parameter estimating [31]. ANFIS is a fuzzy Sugeno put in the framework of adaptive systems to facilitate learning and adaptation. Such frameworks make fuzzy logic more systematic and less relying on expert knowledge [34]. The objective of ANFIS is to optimize the parameters of a given fuzzy inference system by applying a learning procedure using a set of input-output training data. Combinations of the least square and back-propagation methods are used for training a fuzzy inference system to enhance its performance [35].

ANFIS is designed as a first order Sugeno fuzzy model so the consequent part of the fuzzy rules is a linear equation with generalized bell-shaped membership functions of the inputs, which contain three fitting parameters; centre and half of the width and slope. Two membership functions were chosen on each input; usually this number is determined experimentally.

The Initialization of the primes parameters of the ANFIS network are set so that the centers of the membership functions are equally spaced along the range of input variable, where the initial value of consequent parameters are assumed zero. The inverse model control approach was used, in which the controller is the inverse of the plant. In this method a learning task is needed to find the inverse model of the advanced biodiesel microwave system so ANFIS inverse learning for control purpose is performed as shown in Fig. 12.

The training data were obtained from real experiments to reflect input-output characteristics of the biodiesel reactor. In the application phase, the obtained ANFIS inverse model was used to generate the control action. Fig. 13 shows the ANFIS controller output under different operation conditions at controller sample interval equal to 5000 ms.

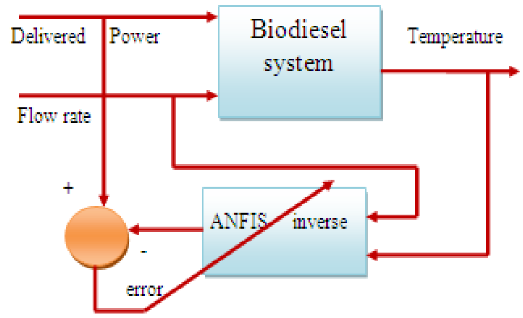


Figure 12. Block diagram for inverse control method.

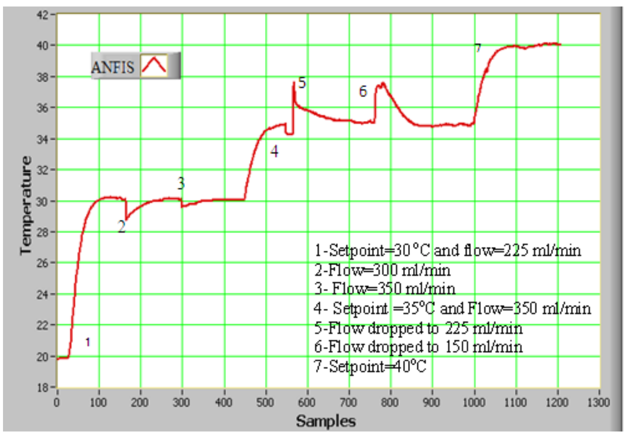


Figure 13. ANFIS controller output under different operation conditions.

D. PID Controller

The proportional, integral, derivative (PID) controller has use in many process control applications [36], due to its simplicity in structure, robustness in a wide range of operating conditions. The implementation of PID controllers retunes their three-term parameters. However, PID controller performs well only at a particular operating range and it is necessary to retune the PID controller if the operating range is changed. The PID controllers do not provide contented results for nonlinear process [37]. The paper presents an adaptive PID controller design. Controller parameters are updated by using ANFIS model and Genetic Algorithm (GA)

The online genetic algorithm proved difficult to test due to the fact that the simulations cannot be run in real time. To prevent any unstable controllers being implemented by the genetic algorithm, the ANFIS model for the microwave biodiesel reactor was used, so now the GA is used as offline stage for tuning the PID parameters based on the model which it is has online updating for changes as shown in Fig.14.

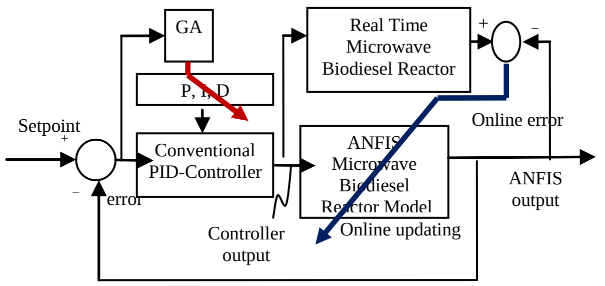


Figure 14. GA use as offline stage for tuning the PID parameters based on ANFIS mode

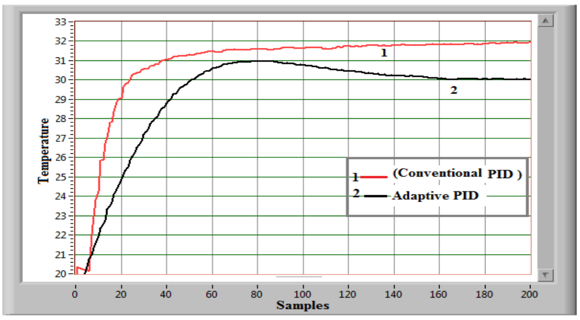


Figure 15. Comparison between adaptive PID and conventional PID controllers (setpoint equal to 30°C)

By tuning the three constants by GA, the controller can provide control action designed for specific process requirements. The response of the controller can be described in terms of the responsiveness of the controller to an error, the degree to which the controller overshoots the setpoint and the degree of system oscillation Fig.15 shows the comparison between the adaptive PID genetically and conventional PID controller for microwave biodiesel reactor at 30°C setpoint, 5000ms sample interval and 300ml/min flow rate.

1) ANFIS Microwave Biodiesel Reactor Model

The ANFIS network is designed to model the microwave biodiesel reactor. In this case the learning task is needed to find the model of the microwave biodiesel system from the real training data (*inlet oil temperatures, inlet oil flow rate, delivered microwave power, output temperature and reflected power)*, so ANFIS is learning for model purpose as shown in figure16.

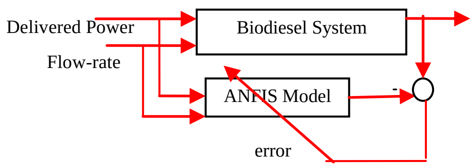


Figure 16. ANFIS model for Real time biodiesel reactor

1) Genetic Algorithms

A GA is typically initialised with a random population for large number of individuals. This population is usually represented by a real-valued number or a binary string called a chromosome. How well an individual performs a task is measured is assessed by the objective function. The objective function assigns each individual a corresponding number called its fitness. The fitness of each chromosome is assessed and a survival of the fittest strategy is applied. In this project, the magnitude of the error will be used to assess the fitness of each chromosome. There are three main stages of a genetic algorithm; these are known as *reproduction*, *crossover* and *mutation*. The GA process in microwave biodiesel reactor is shown in Fig.17

IV. Experimental Results

It was experimentally demonstrated that the controllers can successfully track the demands of reactor temperature setpoint in 5000 ms control sample interval at 300 ml/min flow rate.

The comparison of the controllers subjected to setpoint tracking beginning from inlet oil temperature is illustrated in Fig. 18. Alternatively, multiple setpoint tracking beginning from the nominal temperature value of 30 °C, then rising to 35 °C and followed by going back down to 30 °C are shown in Fig. 19.

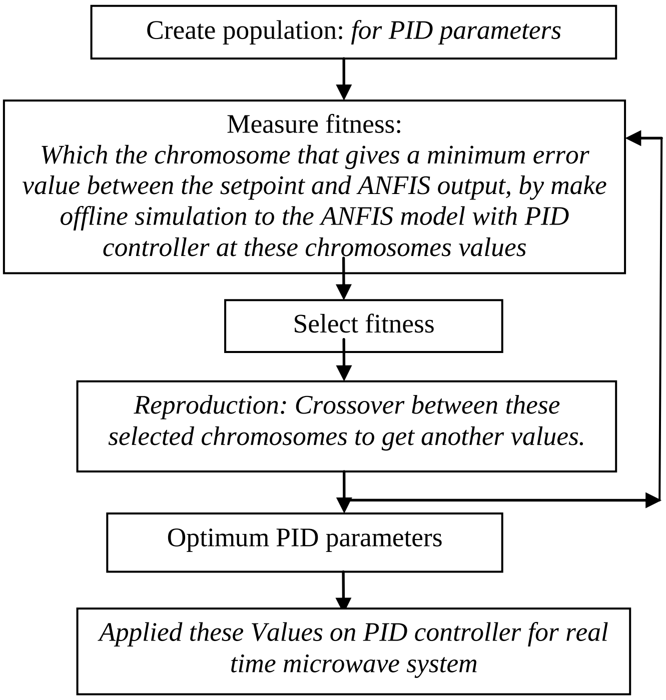
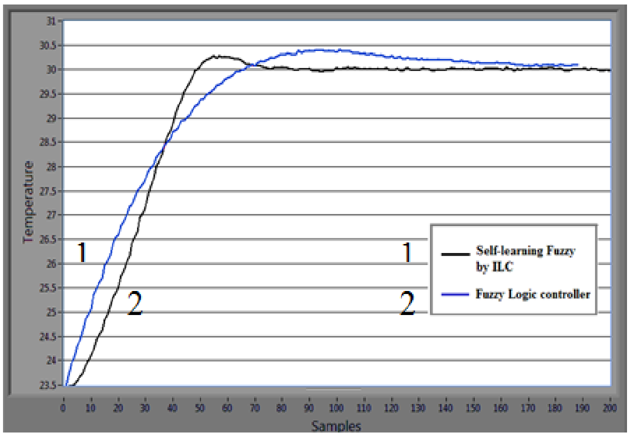
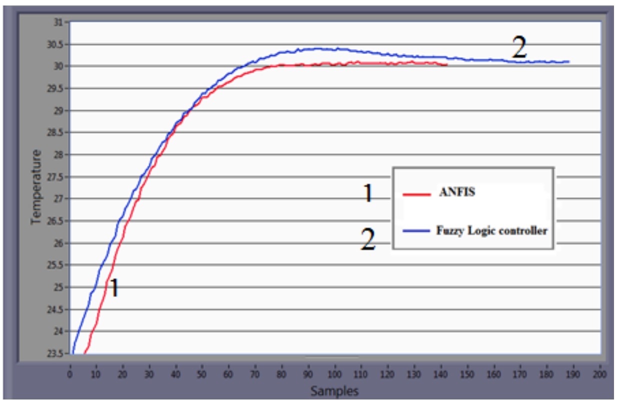


Figure 17. GA process in microwave biodiesel reactor



(a)



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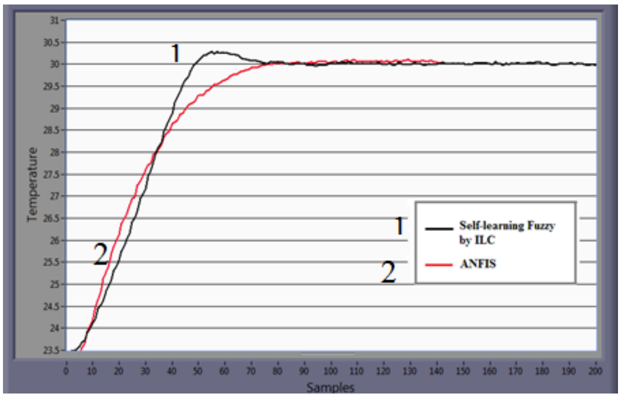
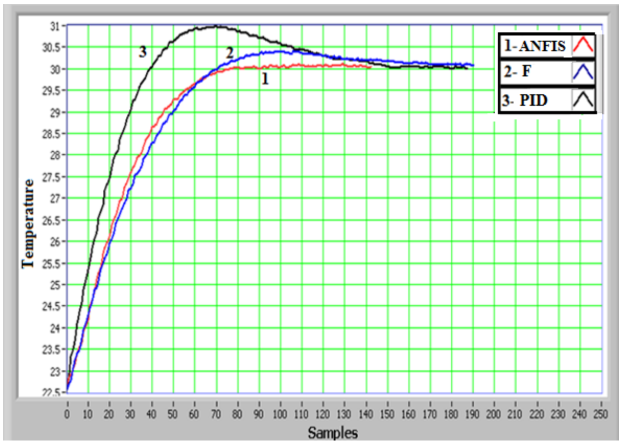
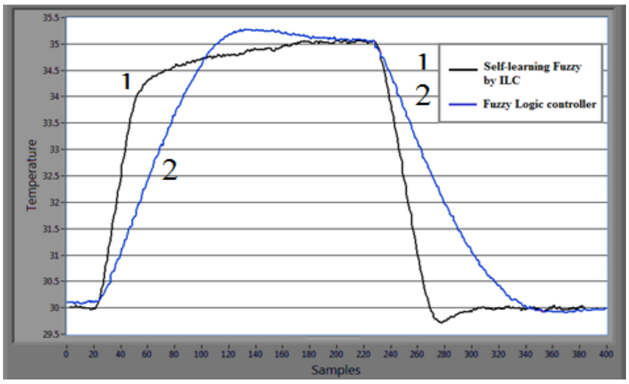


(c)



(d)

Figure 18. Controllers setpoint tracking comparison from inlet temperature, (a) Self-learning using (ILC) controller and conventional fuzzy controller, (b) ANFIS and conventional fuzzy controller, (c) ANFIS and Self-learning using (ILC) controller, (d) ANFIS, conventionaFLC, and PID.



(a)

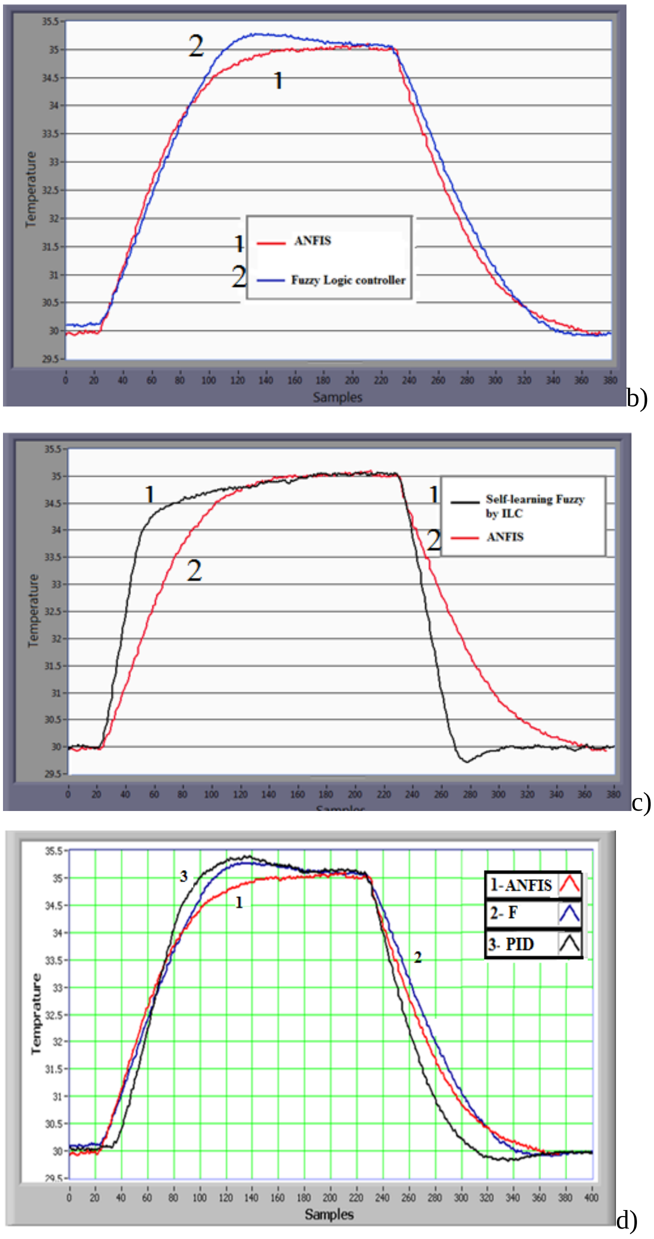


Figure 19. Controllers comparison on multiple sepoint tracking from nominal temperature value, (a) Self-learning using (ILC) controller and conventional fuzzy controller, (b) ANFIS and conventional fuzzy controller, (c) ANFIS and Self-learning using (ILC) controller, (d). ANFIS, conventiona FLC, and PID.

It is evident from these results that the controllers can successfully track the demands of reactor temperature setpoints. The ANFIS and self-learning fuzzy controller improves the conventional fuzzy controller response in three stages: speed to reach the setpoint, the overshoot and steady state error [3].

The developed novel controllers were also tested under an introduced disturbance in the feed to the flow rate of the reactor. After the start up of the processes, the reactor temperature was left regulated by the controllers at 30˚C. The disturbance was then introduced. When the nominal feed in flow rate was reduced by 20% and 10% then sudden rising by 30%, it was observed that the controllers were able to bring back the process to its initial setpoint of 30˚C. ANFIS and self-learning show a good ability to reject these disturbances with less effect as shown in Fig. 20.

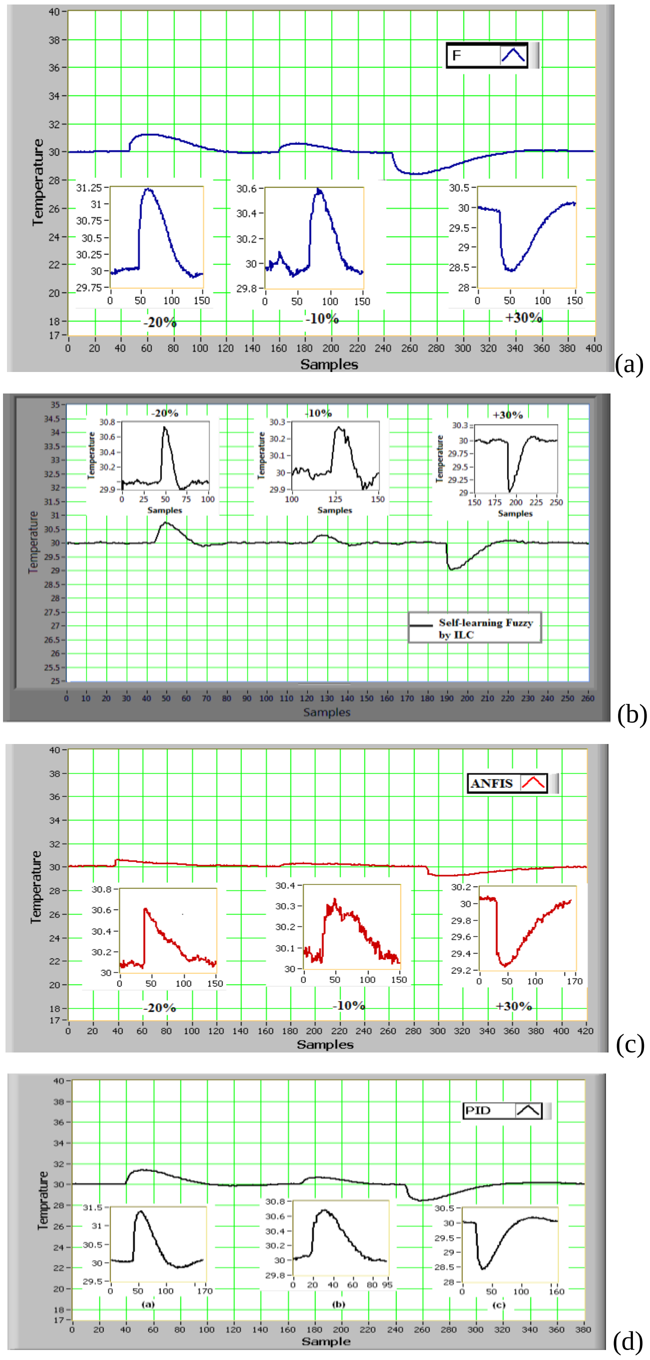
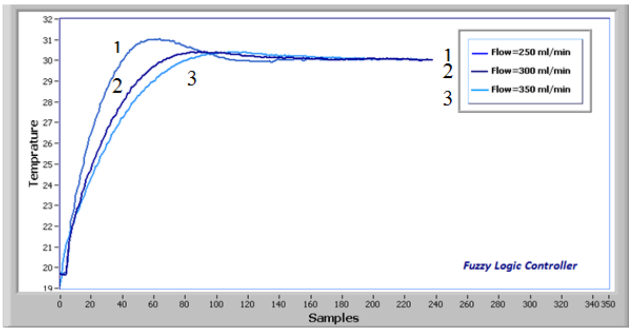
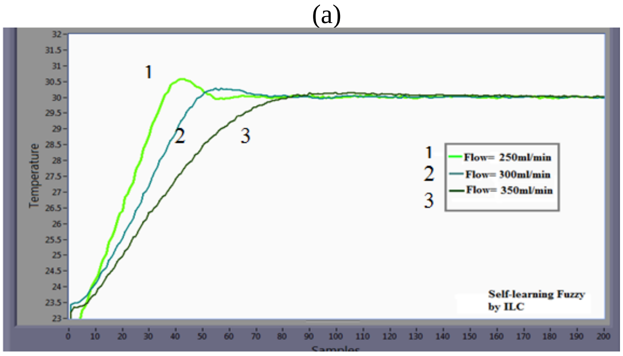


Figure 20. Disturbance rejections for the controllers: (a) Conventional fuzzy controller, (b) Self-learning using (ILC) controller, (c) ANFIS, (d). Adaptive PID controller.

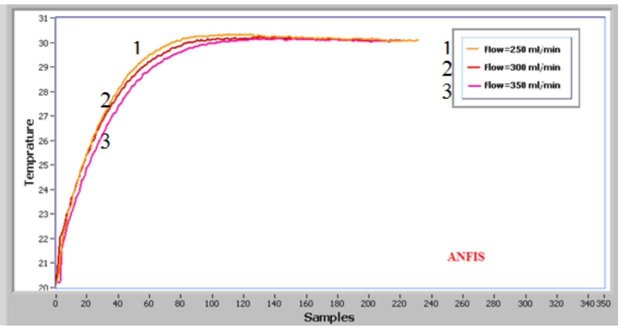
In three different flow rates (250, 300, and 350) ml/min, a performance response of the controllers was tested. Fig. 21 shows that the Neuro-Fuzzy (ANFIS) controller in small value of flow (250 ml/min) can keep on its behavior with small change in its response. That indicates a good repeatability response of the controller at different flow values.



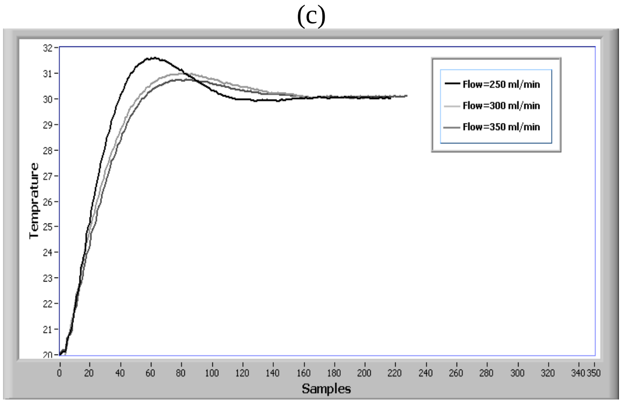
(a)



(b)



(c)



(d)

Figure 21. Performance of the controllers under different flow rate, (a) Conventional fuzzy controller, (b) Self-learning using (ILC) controller, (c) ANFIS, (d). Adaptive PID controller.

V. Conclusions

Three types of intelligent controllers (conventional fuzzy logic, self-learning fuzzy using ILC and ANFIS inverse controller) are online implemented; for real time temperature control in advanced biodiesel microwave reactor. A unique tuning procedure for MFs of fuzzy logic control is proposed using iterative learning technique with small number of rules and straightforward implementation.. A LabVIEW software tool was used for online monitoring. Experimental results reported in this paper indicate that the self-learning using ILC control reduced the order of conventional fuzzy controller with improvements in tracking performance characteristics and disturbances rejection as compared with fuzzy logic and inverse ANFIS.

Adaptive PID controller) genetically by using ANFIS model was online implemented;. The experimental results illustrate that the proposed controllers give good control performance.

References

[1] M. K. Lam, K. T. Lee, and A. R. Mohamed, “Homogeneous, heterogeneous and enzymatic catalysis for transesterification of high free fatty acid oil (waste cooking oil) to biodiesel: A review,” *Biotechnology Advances*, vol. 28, no. 4, pp. 500-518, 2010.

[2] X. Fan, R. I. Burton, and G. Austic, “Preparation and Characterization of Biodiesel Produced from Recycled Canola Oil,” *Open Fuels & Energy Science Journal*, vol. 2, pp. 113-118, 2009.

[3] W. A. Wali, J. D. Cullen, K. H. Hassan *et al.*, "Comparison between Adaptive and Fuzzy logic controllers for advance microwave biodiesel reactor." pp. 23-28.

[4] C. J. Chuck, C. D. Bannister, J. Gary Hawley *et al.*, “Spectroscopic sensor techniques applicable to real-time biodiesel determination,” *Fuel*, vol. 89, no. 2, pp. 457-461, 2010.

[5] V. Rudolph, and Y. He, "Research and development trends in biodiesel," *Developments in Chemical Engineering and Mineral Processing*. pp. 461-474.

[6] H. Y. Kuen, F. S. Mjalli, and Y. H. Koon, “Recursive Least Squares-Based Adaptive Control of a Biodiesel Transesterification Reactor,” *Industrial and Engineering Chemistry Research*, vol. 49, no. 22, pp. 11434-11442, 2010.

[7] F. S. Mjalli, L. K. San, K. C. Yin *et al.*, “Dynamics and control of a biodiesel transesterification reactor,” *Chemical Engineering and Technology*, vol. 32, no. 1, pp. 13-26, 2009.

[8] P. T. Benavides, and U. Diwekar, “Optimal control of biodiesel production in a batch reactor: Part I: Deterministic control,” *Fuel*, vol. 94, pp. 211-217, 2012.

[9] R.-E. Precup, and H. Hellendoorn, “A survey on industrial applications of fuzzy control,” *Computers in Industry*, vol. 62, no. 3, pp. 213-226, 2011.

[10] B. M. Dehkordi, A. Kiyoumarsi, P. Hamedani *et al.*, “A comparative study of various intelligent based controllers for speed control of IPMSM drives in the field-weakening region,” *Expert Systems with Applications*, vol. 38, no. 10, pp. 12643-12653, 2011.

[11] C. Boldisor, V. Comnac, I. Topa *et al.*, “A Self-Learning Based Fuzzy Controller for DC Drive Control,” *Bulletin of the Transilvania University of Brasov, Engineering Sciences*, vol. 52, pp. 221-226, 2010.

[12] R. Dehini, B. Ferdi, and B. Bekkouche, “Fuzzy Logic Controller Optimization Based on GA for Harmonic Mitigation,” *Journal of Artificial Intelligence*, vol. 5, no. 1, pp. 26-36, 2012.

[13] M. Tinkir, “A new approach for interval type-2 by using adaptive network based fuzzy inference system,” *International Journal of the*

Physical Sciences, vol. 6, no. 19, pp. 4502-4518, 16 September, 2011, 2011.

[14] C.-J. Chien, S.-Y. Peng, and Y.-C. Wang, "Design and implementation of type-2 fuzzy iterative learning controllers using FPGA chip," *Proceedings of the 2011 IEEE 5th International Conference on Cybernetics and Intelligent Systems, CIS 2011.* pp. 208-213.

[15] E. Leal, K. M. S. Viana, R. H. G. A. Kiminami *et al.*, "Preparation of ZnAl2O4 catalytic support by combustion reaction: Influence of type of heating source," *Nanotechnology 2010: Advanced Materials, CNTs, Particles, Films and Composites - Technical Proceedings of the 2010 NSTI Nanotechnology Conference and Expo, NSTI-Nanotech 2010.* pp. 502-505.

[16] D. Kim, J. Choi, G.-J. Kim *et al.*, "Accelerated esterification of free fatty acid using pulsed microwaves," *Bioresource Technology,* vol. 102, no. 14, pp. 7229-7231, 2011.

[17] G. Patterson, "Modeling and scale-up of mixing- and temperature-sensitive chemical reactions," *Industrial and Engineering Chemistry Research,* vol. 44, no. 14, pp. 5325-5341, 2005.

[18] M. P. Dinca, M. Gheorghe, M. Aherne *et al.*, "Fast and accurate temperature control of a PCR microsystem with a disposable reactor," *Journal of Micromechanics and Microengineering,* vol. 19, no. 6, 2009.

[19] P. Bhatt, R. Roy, and S. P. Ghoshal, "GA/particle swarm intelligence based optimization of two specific varieties of controller devices applied to two-area multi-units automatic generation control," *International Journal of Electrical Power and Energy Systems,* vol. 32, no. 4, pp. 299-310, 2010.

[20] C.-J. Lin, and Y.-J. Xu, "A novel genetic reinforcement learning for nonlinear fuzzy control problems," *Neurocomputing,* vol. 69, no. 16-18, pp. 2078-2089, 2006.

[21] C. Le, G. Baoming, and A. T. De Almeida, "Self-tuning PID temperature controller based on flexible neural network," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics).* pp. 138-147.

[22] C.-J. Lin, and C.-Y. Lee, "Non-linear system control using a recurrent fuzzy neural network based on improved particle swarm optimisation," *International Journal of Systems Science,* vol. 41, no. 4, pp. 381-395, 2010.

[23] A. Pal, and R. Mudi, "Speed Control of DC Motor using Relay Feedback Tuned PI, Fuzzy PI and Self-Tuned Fuzzy PI Controller," *Control Theory and Informatics,* vol. 2, pp. 24-32, 2012.

[24] J. X. Xu, S. K. Panda, and T. H. Lee, *Real-Time Iterative Learning Control: Design and Applications*: Springer, 2008.

[25] I. Ursu, and A. Toader, "A unitary approach on adaptive control synthesis," *12th WSEAS International Conference on Mathematical Methods, Computational Techniques and Intelligent Systems, MAMECTIS '10.* pp. 71-78.

[26] S. Ertunc, B. Akay, H. Boyacioglu *et al.*, "Self-tuning control of dissolved oxygen concentration in a batch bioreactor," *Food and Bioproducts Processing,* vol. 87, no. 1, pp. 46-55, 2009.

[27] A. Boubakir, S. Labiod, and F. Boudjema, "A stable self-tuning proportional-integral-derivative controller for a class of multi-input multi-output nonlinear systems," *JVC/Journal of Vibration and Control,* vol. 18, no. 2, pp. 228-239, 2012.

[28] H. Zhu, L. Li, Y. Zhao *et al.*, "CAS algorithm-based optimum design of PID controller in AVR system," *Chaos, Solitons and Fractals,* vol. 42, no. 2, pp. 792-800, 2009.

[29] R. Alcalá, J. Alcalá-Fdez, M. Gacto *et al.*, "Improving fuzzy logic controllers obtained by experts: a case study in HVAC systems," *Applied Intelligence,* vol. 31, no. 1, pp. 15-30, 2009.

[30] V. P. Battula, V. Kumar, and V. Suryanarayana, "Intelligent control of synchronous machines using ANFIS and model reference neural network controller," *ICWET 2010 - International Conference and Workshop on Emerging Trends in Technology 2010, Conference Proceedings.* pp. 635-639.

[31] S. Soyguder, and H. Alli, "An expert system for the humidity and temperature control in HVAC systems using ANFIS and optimization with Fuzzy Modeling Approach," *Energy and Buildings,* vol. 41, no. 8, pp. 814-822, 2009.

[32] S. Soyguder, M. Karakose, and H. Alli, "Design and simulation of self-tuning PID-type fuzzy adaptive control for an expert HVAC system," *Expert Systems with Applications,* vol. 36, no. 3, Part 1, pp. 4566-4573, 2009.

[33] J.-S. R. Jang, "ANFIS: adaptive-network-based fuzzy inference system," *IEEE Transactions on Systems, Man and Cybernetics,* vol. 23, no. 3, pp. 665-685, 1993.

[34] K. Assaleh, "Extraction of Fetal Electrocardiogram Using Adaptive Neuro-Fuzzy Inference Systems," *Biomedical Engineering, IEEE Transactions on,* vol. 54, no. 1, pp. 59-68, 2007.

[35] M. Shahlaei, A. Madadkar-Sobhani, L. Saghaie *et al.*, "Application of an expert system based on Genetic Algorithm–Adaptive Neuro-Fuzzy Inference System (GA–ANFIS) in QSAR of cathepsin K inhibitors," *Expert Systems with Applications,* vol. 39, no. 6, pp. 6182-6191, 2012.

[36] L. Coelho, M. Pessôa, "A tuning strategy for multivariable PI and PID controllers using differential evolution combined with chaotic Zaslavskii map", Expert Systems with Applications,Vol.38, PP.13694-13701, 2011.

[37] N.Kamala, "Multivariable control of nonlinear process using soft computing techniques", Journal of Advances in Information Technology, Vol. 3, 2012.