ADCAIJ: Advances in Distributed Computing and Artificial Intelligence Journal
Regular Issue, Vol. 9 N. 1 (2020), 29-50
eISSN: 2255-2863
DOI: https://dx.doi.org/10.14201/ADCAIJ2020912950

Application of DCS for Level Control in Nonlinear System using Optimization and Robust Algorithms

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KEYWORD

DCS; SCADA; Distributed Control; Genetic Algorithm; Quantitative Feedback Theory; PSO; MIMO; Nonlinear System; PI Controller; Level Process

ABSTRACT

This proposed work deals with the real-time implementation of a Proportional-Integral (PI) level controller for a nonlinear interacting Multi-Input Multi-Output (MIMO) system using the YOKOGAWA CENTUM CS 3000 Distributed Control System (DCS). Some advanced algorithms were chosen to tune the PI controller, presuming the effect of disturbances in a nonlinear interacting MIMO system. Three algorithms; a classical evolution algorithm, Genetic Algorithm (GA); a metaheuristic optimization algorithm, Particle Swarm Optimization algorithm (PSO); a robust algorithm, Quantitative Feedback Theory (QFT); were chosen for optimal offline tuning of the controller. These controllers were then implemented using a DCS, and the simulation results resulting from the three algorithms were compared with the experimental results. The impact of the tuning algorithms on the controller performance was studied in real-time.

1. Introduction

Level control is among the oldest industrial task, which, despite being modernized, is still prevalent in researchers' apprehension as the failure or breakdown of a level control system may cause fatal damage to equipment and may lead to production inertia. Hence, a reliable, integrated, and advanced control setup is preferable in such industrial processes. Therefore, several attempts have been made to find a suitable control methodology which would fully cover the dynamic, complex, and nonlinear characteristics of a real-time process (Kiruthika et al., 2015; Kolmare et al., 2017; Sukalkar, 2016) and one of the most widely preferred methods to achieve adequate control of fluid level in processes is to implement controllers as Distributed Control Systems (DCS). DCS is widely utilized in processes with a large number of Inputs and Outputs (I/O), which needs to be controlled automatically with faster and remote data acquisition (Bailey and Wright, 2003; Sinopoli et al., 2003; Wu et al., 2008). According to Sbárbaro and Villar (Sbárbaro and Villar, 2010), the main tasks of distributed control systems in any industrial process is to ensure that the process data is acquired within a reasonable time frame and that timely actions are taken through a series of activities, technically defined as Human-Machine Interface (HMI), data acquisition and processing, communication and control and process analysis, and optimization to sustain the stability in the process. In a DCS, a current loop signal of 4-20 mA is transmitted over a 5-10 V signal, and all the analog and digital I/O, operator terminal, supervisory terminal, and data repository are connected along with the Ethernet network, thereby ensuring the efficient transmission of data and data security and integrity. In this system, each node is independent but also integrated through the network. Due to its distributed setup, DCS utilizes less space and facilitates easy installation (YOKOGAWA; YOKOGAWA India Ltd., 2009).

DCS is usually implemented in three levels in processes (Galloway and Hancke, 2013); Level 1 is the field level which comprises of measuring devices, sensors, transmitters, actuators, and other final control elements; Level 2 is the plant supervisory level where the control logic is designed, developed and configured in the workstation and system servers; Level 3 is the coordination or control level which acts as an interface between the field level and supervisory operator level to interact with the process and operate it accordingly. The operation of each level in DCS is supervised by a Real-Time Operating System (RTOS), and all the levels communicate with each other through the network protocol in the DCS, namely, field bus and process bus protocols (Gupta and Chow, 2010; Ion Marian, 2015; Knapp and Langill, 2015; Runceanu and Popescu, 2010). The Supervisory Control And Data Acquisition system (SCADA) situated in the Level 2 of DCS architecture possesses several Remote Terminal Units (RTU) which acquires the digital and analog data from the sensors and actuators located in the field level and communicate the data to the coordination level through the DCS network. Each of the components in the DCS possesses requisite specifications to convert the signal to specific standards and units (Choi, 2002). The major convenience of using DCS for controlling a process is that its control module is distributed, and each module performs a redundant control task, thereby leading to reduced downtime in the event of a failure of a control module and ensuring capable and uninterrupted control reliability.

In this work, multiloop Proportional-Integral (PI) controller tuned using robust and optimization algorithms were implemented in a nonlinear interacting conical tank level system using YOKOGAWA DCS. The paper's contents are structured as follows; section 2 gives a brief overview of the different control techniques employed in complex nonlinear Multi-Input Multi-Output (MIMO) systems. Section 3 describes the process in which DCS based control is implemented, and section 4 describes the specifications and features of YOKOGAWA CENTUM CS 3000 DCS. In section 5, a detailed description of the controller implementation in DCS is provided. Section 6 elucidates the impact of the different robust and optimization controllers on the process output. Section 7 compares the experimental results with the simulation results of the plant model. Section 8 explains some of the limitations of this research work, and finally, concluding opinions are provided in section 9.

2. Study on Control Techniques in Nonlinear MIMO Systems

Most of the industrial processes are nonlinear, with substantial time delays, measurement delays, dead time, uncertainties, noise, sensor and output disturbance, and PI or Proportional-Integral-Derivative

(PID) controllers in feedforward or feedback control loops are most widely preferred to control such real-time industrial processes owing to its reliability and simplicity in design and implementation. Despite its extensive usage in industrial process control, the capacity of PID controllers is underutilized, and researchers are continuously working on improving the tuning methods or implementation methods to enhance the control capability of PID controllers (Åström and Hägglund, 2006; Ogata, 1995; Vilanova and Visioli, 2012). But, based on the previously published literature on the implementation of PID controllers in dynamic nonlinear systems with numerous process variables and inherent interaction effect, researchers have observed that the PID controllers tuned using traditional tuning rules are not appropriate for extensive process control as they fail to attain the desired results, except for in the lower hierarchy levels (Pérez-Correa et al., 1998; Shean and Cilliers, 2011; Suichies et al., 2000). A major problem with controlling complex nonlinear processes through traditional Single-Input Single-Output (SISO) PID loops emerges from the presence of a large number of manipulated process variables with only a relatively few functional outcomes (Desbiens et al., 1994). Moreover, the multivariable and extremely nonlinear nature of a MIMO process, along with its complex dynamics and substantial delays, make the traditional PID algorithm inappropriate for control (Suichies et al., 2000). Osorio et al. (Osorio et al., 1999) reported that the traditional PID control technique had shown poor efficiency and lack of robustness over narrow operating regions in complex nonlinear real-time plants. Therefore, these authors suggest implementing more sophisticated control algorithms for achieving robust control in real-time plants. Furthermore, traditional control methods necessitate a detailed understanding of the process dynamics, and if all the relevant details of the process are not completely available, then reasonable estimates are considered, and, if the information available is fuzzy or unclear, or incomplete, the traditional controllers may not yield desirable results. Besides, the traditional control methods are primarily based on the premise that the plant's operation is linear and time-invariable, which does not apply to most actual processes. Meanwhile, intelligent control strategies have capabilities that efficiently cope with inadequate plant knowledge and the presence of unexpected or unknown disturbances (Karray and Silva, 2004). According to Zhang (Zhang, 2010), intelligent control is a methodology where control techniques are formulated to replicate the essential features of human intelligence. These features include processing enormous quantities of data, learning, adaptation, and performing adequately under high uncertainty. When addressing process operations from the point of view of plant efficiency, a fast, accurate, and adaptive system reaction is an important demand. As a result, the need to create and use advanced control methods is even greater now. Hence, it can be asserted that intelligent techniques contribute to the control of nonlinear MIMO systems via a structured approach. It is a definition under which the components of the process and the rules they are subjected to are no longer treated as theoretically defined. At the same time, using intelligent control, a suitable solution to the actual dynamic conditions of the process variables, and, thereby the optimum control, cannot be attained by simply solving a set of equations, but rather through a systematic approach. Accordingly, intelligent methods are increasingly being used across alternative approaches such as modeling, industrial process control, and optimization, and, even though the applications handled by intelligent systems are varied, the capacity to process inaccurate, vague, and undefined information is similar. Thwaites (Thwaites, 2007) suggested that the selection of control methods between PID and other advanced methods depends on the knowledge of the process dynamics and all its inherent interactions. Other researchers (Pérez-Correa et al., 1998; ROJAS and CIPRIANO, 2011) also point out that advanced techniques such as intelligent and robust methods produce much better results in controlling complex nonlinear MIMO processes. Some authors found MIMO controllers more suitable for controlling nonlinear dynamic, complex systems. For example, for a complex nonlinear system, Kämpjärvi and Jämsä-Jounela (Kämpjärvi and Jämsä-Jounela, 2003) compared MIMO and SISO control strategies, and the control efficiency of the MIMO controllers was shown to be substantially better than that of the traditional SISO controller. Besides, Jämsä-Jounela et al. (Jämsä-Jounela et al., 2003) implemented multiple SISO PID control systems to gain insight into the performance of PID controllers and claimed that these systems could enhance process control of MIMO systems. Bergh et al. (Bergh et al., 1999) proposed the distributed control systems to be inadequate in achieving satisfactory outcomes using either SISO or MIMO control loops. Therefore, supervisory control systems with various other attributes are desired, and such systems should be adaptable to various computing platforms and should also provide control modules for process data validation, detection of operation faults, and instrumentation problems. These supervisory control systems should also coordinate all the local control loops under its control strategy. Thus, the control of nonlinear MIMO systems using DCS in industrial environments is challenging and, in addition to PID controllers, other advanced process control methods like fuzzy logic, artificial neural networks, metaheuristic and optimization algorithms, robust and adaptive control methods that enhance the controller's capability are adopted (Asadipooya and Safavi, 2016; El-Shafei et al., 2017).

But there are some limitations in the technological aspects of the hardware and software in DCS, which is a significant impediment in the implementation of such computationally extensive and complex control theories in a distributed control system (Luo and Song, 2014; Mousavi et al., 2011). Therefore it is essential to select an effective control strategy by recognizing the strengths and weaknesses of the selected control technique in the control of a nonlinear MIMO system after due consideration of the limitations in the hardware and software technology in a DCS system so that the chosen control strategy becomes the most optimal choice to draw the desired output from the plant. Bergh and Yianatos (Bergh and Yianatos, 2011) established that the essential aspects for the effective utilization of control strategies include knowledge of the process dynamics and the quality of the acquired process data. They observed that a suitable control strategy for a system must be chosen after considering both the measuring instrumentation and the process dynamics. Ultimately, advanced control techniques play a crucial role when contemplating changes in plant operation and its performance. Issues on the appropriateness and feasibility of these advanced control techniques in a complex nonlinear MIMO system were presented in a paper published by Jonas and Craw (Jonas and Craw, 2012). They elucidated that the selected control technique must be efficient to handle the dynamic conditions of a nonlinear system. They must also be capable of interfacing with the measurement instrumentation and sensors in the plant hardware quickly with the available local resources. Moreover, the efficiency and sustainability of the chosen advanced control technique in a plant situated in a remote location should also be carefully considered as continuous technical support may not be feasible in a remote location. Thus, the chosen control technique should generate desired outcomes from the plant by optimizing the process in real-time and stabilizing the plant operation in the event of disturbances while requiring only minimal technical support for implementation and operation in remote locations. Jonas and Craw also summarized that the traditional control techniques were not suitable for generating the desired output in a real-time nonlinear MIMO system with dynamic characteristics and interaction effect. Instead, intelligent control techniques like fuzzy logic, expert systems, artificial neural networks, metaheuristic and optimization algorithms, adaptive control methods, and predictive control methods were suitable for complex nonlinear MIMO systems with minimal variable interactions. In the case of complex systems with numerous variable interactions, a multivariable control strategy was used predominantly to implement effective control action in the process.

The views of Hodouin et al. (Hodouin, 2011) must also be considered before choosing an advanced control technique for a plant. Hodouin et al. (Hodouin, 2011) argued that the primary behavior of even advanced control and optimization techniques could be undermined depending on the mathematical model representing the static and dynamic characteristics of the process. This is because the mathematical models are usually inaccurate when the system is highly complex and nonlinear and characterized by uncertainties. In the case of such a system, a robust control technique insensitive to the changes in the system's mathematical model due to uncertainties is preferred. Taking account of the facts and the relevant literature, in this work, a classical evolution algorithm, Genetic Algorithm (GA); a metaheuristic optimization algorithm, Particle Swarm Optimization algorithm (PSO); and a robust algorithm, Quantitative Feedback Theory (QFT) were chosen to tune the two Multi-Input Single-Output (MISO) controllers, and the influence of these intelligent and robust control algorithms in a real-time nonlinear MIMO plant is analyzed.

3. Process Hardware

A nonlinear interacting Two-Input Two-Output (TITO) conical tank level system was controlled by a multiloop PI controller developed in CENTUM CS 3000 DCS. The fluid level in each conical tank in the plant is measured by orifice plates and Differential Pressure Transmitters (DPT). The final control elements are the two Variable Speed Drive (VSD) pumps situated at the inlet of the tanks. The VSD pumps have a rated speed of 6500 rpm and can provide a flow rate of 0 - 200 cm^3/s or 0 - 720 lph corresponding to an applied input of 0 - 10 V to its thyristor driver circuit. The local plant was connected to the DCS station through I/O wirings and network lines. The analog sensor data, 4 - 20 mA, from the local plant was fed to the DCS and scaled and visualized as trends or graphs. The analog value was then converted to digital value through a 12-bit Analog-to-Digital Converter (ADC). The corresponding controller gain resulting from the robust and optimization algorithms was fed to the two controllers. The controller output was then converted to an analog value of 0 - 10 V through a 12-bit Digital-to-Analog Converter (DAC) and fed to the thyristor driver circuit of the VSD pump, which consequently altered the flow rate of the pump and consequently maintained the level of the fluid between 0 - 30 cm in the tanks. Figure 1 shows a photograph of the local plant on which multiloop PI DCS was implemented.

The empirical modeling and the study of interaction and input-output pairing in the proposed nonlinear MIMO interacting conical tank system are explained in detail in the author's previous publication (Aparna et al., 2018), which can be referred for a comprehensive description and understanding of the process dynamics. To summarize, the proposed system was split into three operating regions, with the operating range in tank 1 ranging between 2 and 13 cm, 13 and 28 cm, and 28 and 44 cm. Similarly, the operating range in tank 2 was split between 3 and 11 cm, 11 and 17 cm, and 17 and 23 cm. The system was modeled as two loops with their respective disturbance blocks, and based on the interaction analysis carried out using Relative Gain Array, Niederlinski Index, and Condition Number, it was inferred that the system is controllable in operating region 1 and 2. In contrast, the system would be difficult to be controlled in operating region 3 (Aparna et al., 2018).

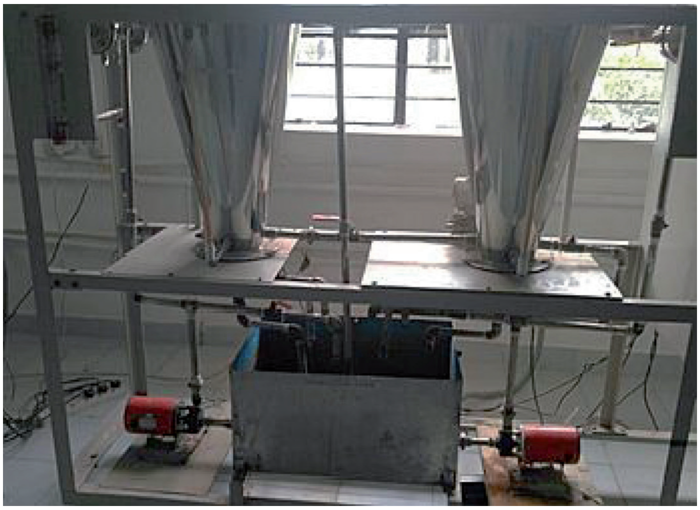

Figure 1: Interacting two-input two-output conical tank level station

4. Yokogawa Centum CS 3000 DCS

Yokogawa Centum CS 3000 DCS is an integrated control setup used to control large-scale and medium-scale industrial processes. Centum CS 3000 DCS mainly comprises of Human Interface Station (HIS), Engineering Workstation (ENG), Field Control Station (FCS), and Communication Network. Centum CS 3000 DCS supports about 100,000 tags and supports interface with about 16 HIS/ Domains.

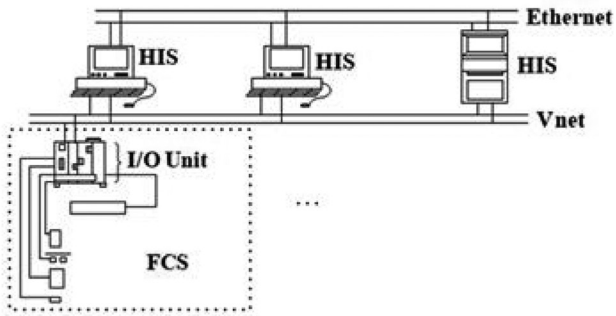

Figure 2: Schematic Diagram of Centum CS 3000 DCS

4.1. Human Interface Station

The human interface station displays the various parameters of the process such as the process variables, manipulated variables, controller gain parameters, trends, and alarms, which helps to understand the current status of the process. The HIS can be used to monitor the process parameters as well as to edit and access the trends, alarms, messages, and process variables.

4.2. Engineering Workstation

Engineering Workstation comprises of engineering software to emulate the control station and for maintenance and system generation. In some DCS, the HIS acts as the Engineering Workstation if it were preloaded with the Engineering software.

4.3. Field Control Station

It is the most crucial component in DCS. Field Control Station executes the control functions to control the process. It usually comprises redundant power supply units, redundant processors, I/O interface, and network coupler units.

4.4. Communication Network

Centum CS 3000 DCS uses Ethernet and Vnet/VLnet for data communication. Ethernet connects HIS, ENG, or any other supervisory computers and has a transmission speed of 1 Gbps with DCS and 100 Mbps with equipment. Vnet/VLnet is used for communicating control data between hardware and for communication with Ethernet and has a redundant bus network with a line speed of 1 Gbps.

The salient features of the communication network are that its Ethernet network supports Bus type or Multi-drop type architecture and can communicate over a distance of 500 m - 2.5 km at a rate of 1 Gbps. Vnet/VLnet also supports Bus type or Multi-drop type architecture and can communicate over a distance of 500 m - 20 km at a rate of 100 Mbps and 1 Gbps.

5. Control System Modeling

In the proposed system, the output of the differential pressure transmitters in the plant was fed as the input to the DCS, and the output of the DCS manipulated the speed of the VSD pumps and thereby the inflow rate to the tanks in the system to maintain the fluid level in the tanks. The corresponding controller gains resulting from GA, PSO, and QFT algorithms (section 6) were employed to control the process fluid level using the DCS.

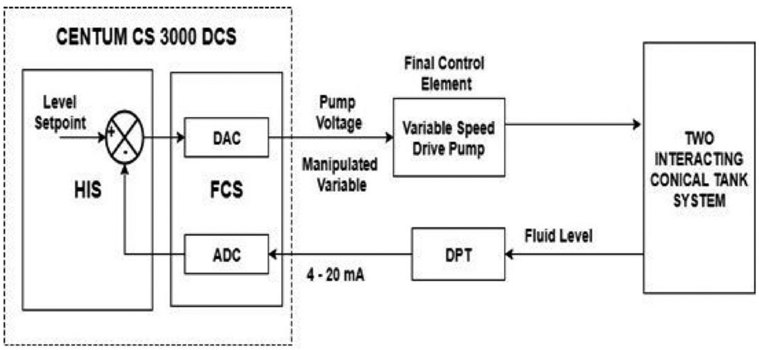

Figure 3: Plant control using Centum CS 3000 DCS

ADCAIJ: Advances in Distributed Computing and Artificial Intelligence Journal
Regular Issue, Vol. 9 N. 1 (2020), 29-50
eISSN: 2255-2863 - https://adcaij.usal.es
Ediciones Universidad de Salamanca

5.1. I/O Assignment

The local plant sensor and transmitter were connected to the DCS panel, as shown in Figure 4. After all the I/O tags were added to the system, the process's functional block diagram was drawn by incorporating all the inputs and outputs of the process, as shown in Figure 5.

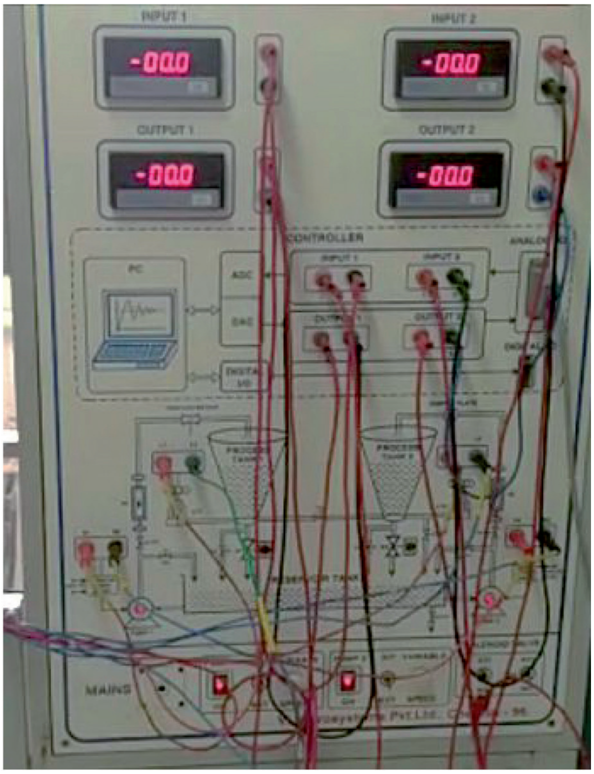

Figure 4: Wiring connections between local plant sensor and transmitter and DCS

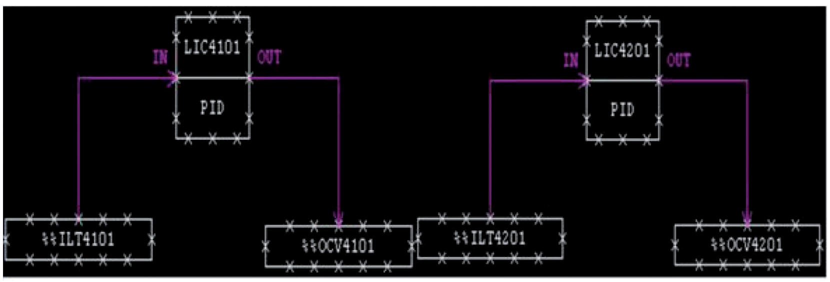

Figure 5: Functional Block Diagram of the multiloop PI control module

5.2. SCADA Design

A graphical representation of the system was built, and the graphical controller was designed, as shown in the following Figure 6. The controller configuration and gains were varied by clicking on the faceplate in the graphic diagram. After changing the controller gains (Rashid et al., 2013), the corresponding trends were recorded.

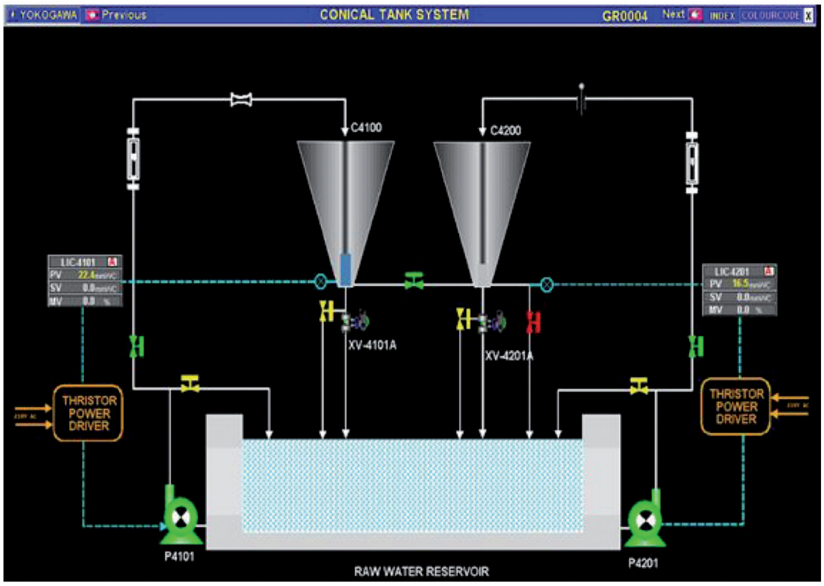

Figure 6: Graphical representation of the plant and control module

6. Controller Tuning and Experimental Results

The DCS controller gains were varied based on different algorithms, GA, PSO, and QFT, and the accuracy and effectiveness of these algorithms in controlling the level of the tanks in this nonlinear process were found out by analyzing the results obtained for different setpoints.

6.1. Genetic Algorithm

In GA, Integral Time-weighted Absolute Error (ITAE) was considered the algorithm's optimization function, and the controller parameters were determined for the minimal ITAE value. One iteration completed one generation of the genetic algorithm, and optimization was performed for several generations until admissible gains in the controller, which reduced the system error, were attained. Sensitivity analysis was performed for various population sizes, crossover, and mutation probabilities, and the best results for this approach were obtained in 500 iterations for a single point crossover process with a likelihood of 0.1 and a uniform mutation likelihood of 0.03. An initial population size of 200 and a mixture of elitism and stochastic uniform methods of selection were employed.

6.2. Particle Swarm Optimization Algorithm

A combination of rise time, settling time, overshoot, and undershoot in the system response was assumed as the optimization function for this algorithm. The minimum optimization function was determined with an initial swarm population of 200. The initial velocity of a particle was assumed to be 0.9, and the weight constants for the individual best position of the particle and the global best position in the search space were assumed to be 2.0 each, based on sensitivity analysis. The algorithm was implemented for 500 iterations to determine the controller gains corresponding to the minimum optimization function.

6.3. Quantitative Feedback Theory

In this algorithm, plant model templates were created, and the plant model control loop was designed to attain excellent setpoint tracking and input disturbance rejection. A margin value greater than one was assumed, and the boundaries pertaining to the performance specifications were created at different frequencies to design the controller by adding gain and integrator blocks. Even though QFT can be applied to the state-space model or transfer function matrix of the entire MIMO model in an operating region, the QFT controller was designed by considering the system as two MISO loops for easy implementation in the plant hardware. The controller was tuned with QFT principles for setpoint tracking and input disturbance rejection for up to ±50 % uncertainty in the nominal transfer function coefficients.

Given that many researchers have already clarified the theory behind GA, PSO, and QFT in detail, it is not repeated in this article, and the description regarding the implementation of the controllers in the DCS is explained in the following paragraphs. The three algorithms were implemented to control the plant model in simulation (Aparna et al., 2018; Aparna,), and the resulting offline gains were utilized to control the plant in real-time. The offline gains resulting from the implementation of GA based control, PSO based control, and QFT based control in the proposed system are indicated in Table 1. The proportional gain K_p was utilized to compute the Proportional Band (PB). Integral and Derivative gain was assumed to be 1 and 0, respectively, for all the cases of DCS control.

In this experimental test, three sets of the setpoint were considered that encompassed the entire operating range of the process,

- Operating Region 1/Case 1 – Level in Tank 1 and Tank 2 = 12 cm and 10 cm, respectively
- Operating Region 2/Case 2 – Level in Tank 1 and Tank 2 = 25 cm and 12 cm, respectively
- Operating Region 3/Case 3 – Level in Tank 1 and Tank 2 = 30 cm and 18 cm, respectively.

Figure 7 to Figure 9 depicts the system's output response for all the cases of setpoints when multi-loop PI DCS was tuned using GA. Similarly, Figure 10 to Figure 12 and Figure 13 to Figure 15 depicts the system's output response for different setpoints when the controller was tuned using PSO and QFT, respectively. In the following figures, LIC4101 and LIC4201 are the level controllers for the two conical tanks, and the legends PV, SV, and MV stand for Process Value, Set Value, and Manipulated Value, respectively.

Table 1: Proportional Band For DCS Control

Algorithm	*Case*1 (%*PB*)		*Case*2 (%*PB*)		*Case*3 (%*PB*)	
	G11-G21 Loop	G22-G12 Loop	G11-G21 Loop	G22-G12 Loop	G11-G21 Loop	G22-G12 Loop
Genetic Algorithm	13	14	26	55	11	10
Particle Swarm Optimization Algorithm	14	22	22	36	100	15
Quantitative Feedback Theory	49	73	54	97	31	100

6.4. Response of DCS tuned using GA

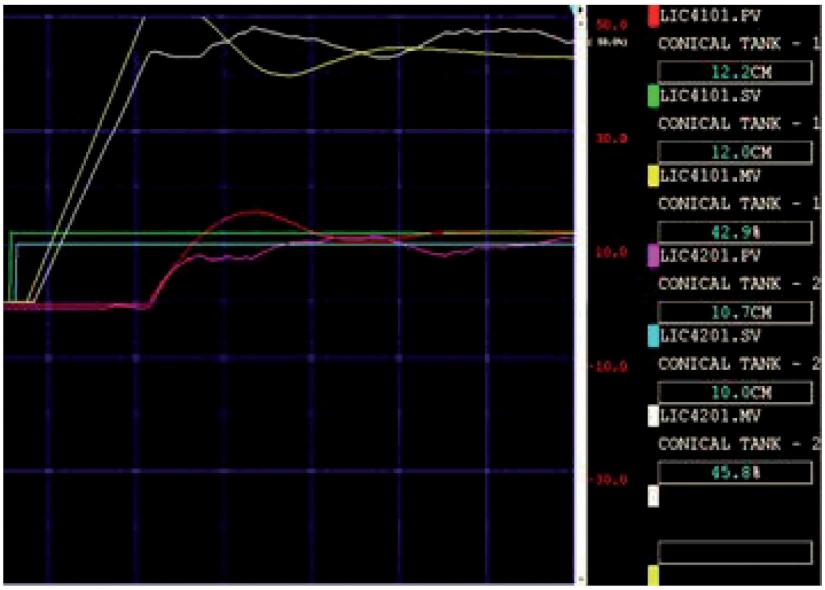

Figure 7: Trend Window - Using GA for Case 1 Setpoint

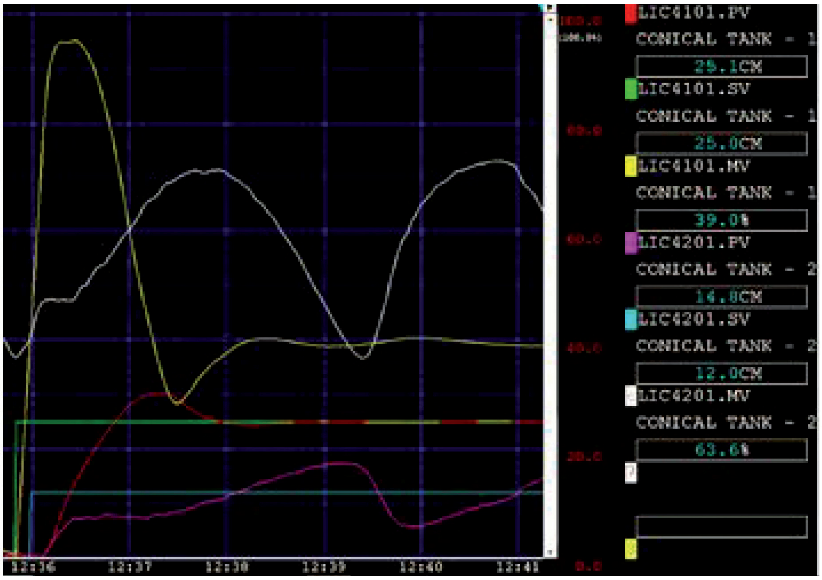

Figure 8: Trend Window - Using GA for Case 2 Setpoint

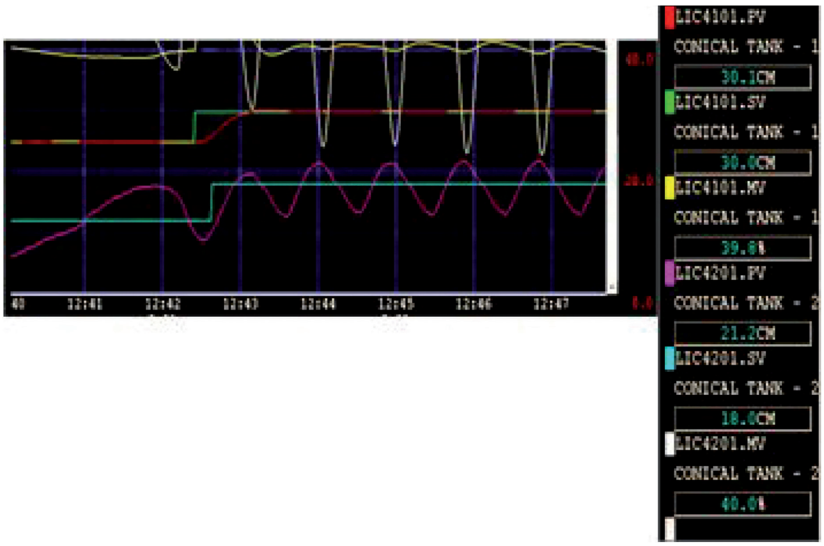

Figure 9: Trend Window - Using GA for Case 3 Setpoint

6.5. Response of DCS tuned using PSO

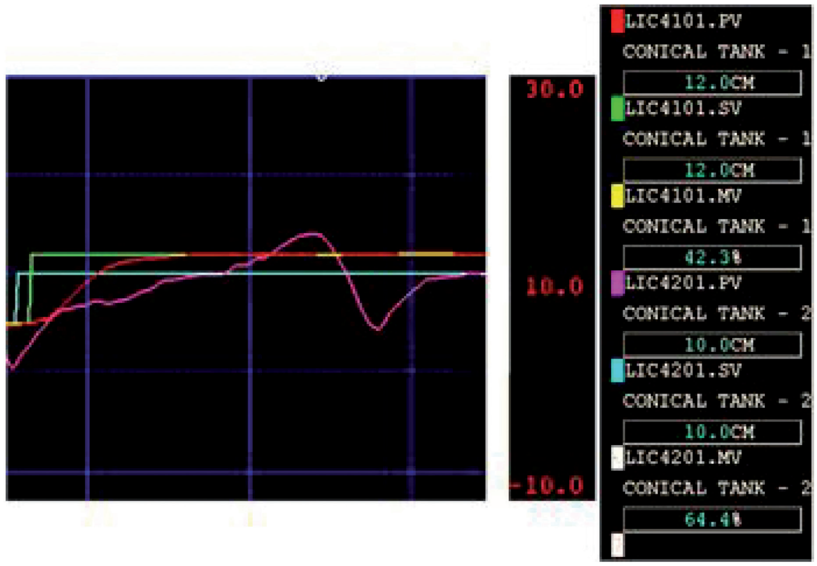

Figure 10: Trend Window - Using PSO for Case 1 Setpoint

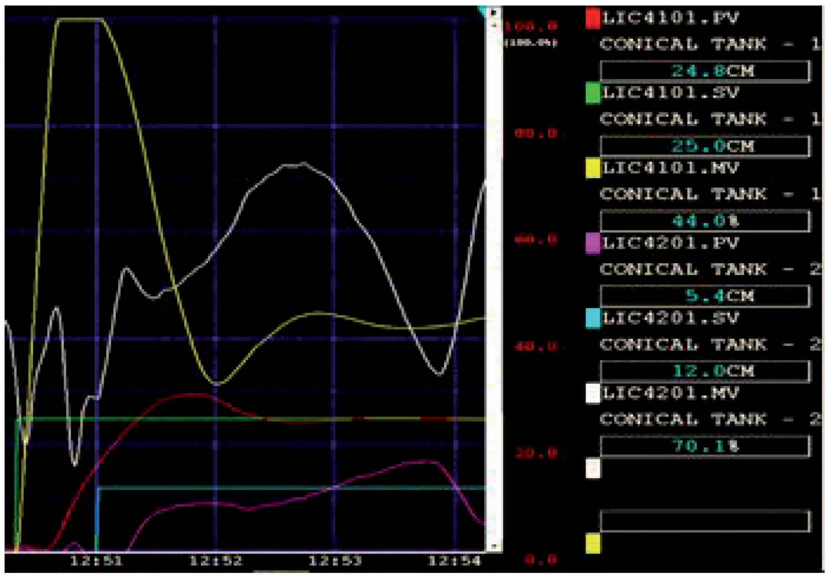

Figure 11: Trend Window - Using PSO for Case 2 Setpoint

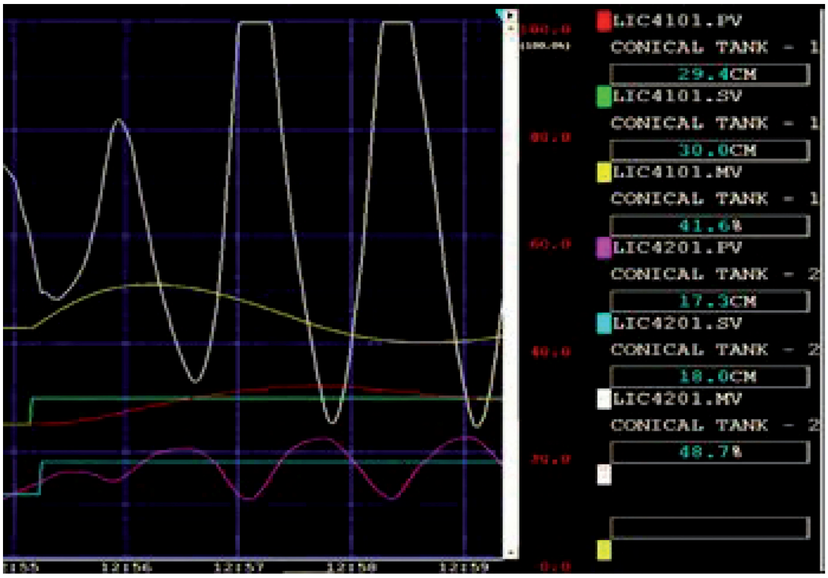

Figure 12: Trend Window - Using PSO for Case 3 Setpoint

6.6. Response of DCS tuned using QFT

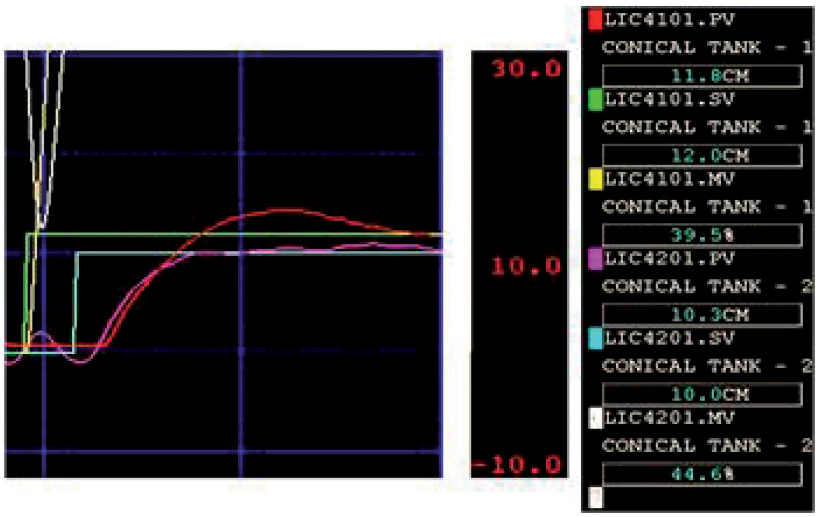

Figure 13: Trend Window - Using QFT for Case 1 Setpoint

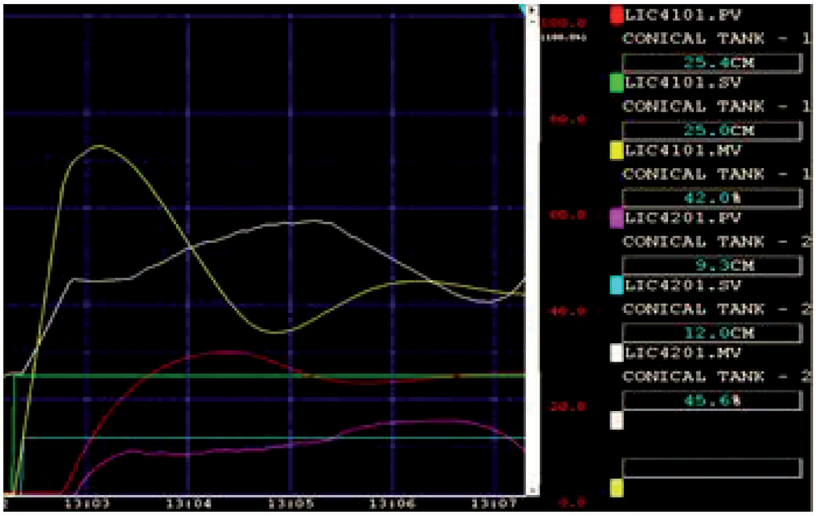

Figure 14: Trend Window - Using QFT for Case 2 Setpoint

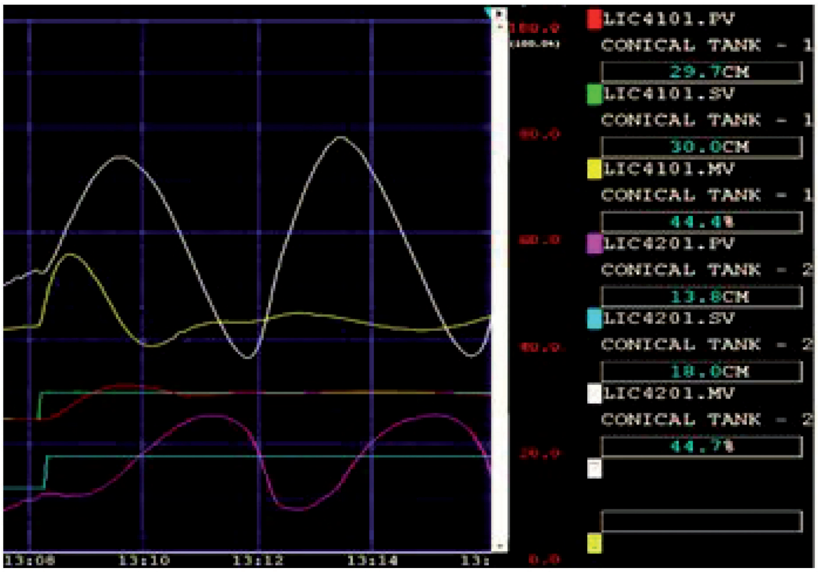

Figure 15: Trend Window - Using QFT for Case 3 Setpoint

7. Discussions

The suitability of the algorithms in the nonlinear MIMO plant was analyzed by comparing the dynamic response of the controlled plant. Comparisons among the controllers' performance specifications were carried out by evaluating the time response characteristics such as rise time, settling time, overshoot, and offset of the process variable. Moreover, a settling band of ±10 % of the Process Variable (PV) was considered to provide a reasonable measure to accommodate the measurement noise. Additionally, just as in most industrial plants, a quick response with little to no overshoot and negligible offset was assumed to be the optimum controller performance. Thus, the controller was tuned to generate an optimal response to ensure no overshoot and quicker settling time in the response plots. The time response characteristics of the controlled system with different controllers were analyzed for both the real-time plant with DCS and for the plant model in simulation to understand the behavior and characteristics of the proposed intelligent and robust algorithms. Table 2 indicates the approximate values of the plant's step response characteristics with DCS and the plant model in the simulation when the controller was tuned with different algorithms and tested with different setpoints.

7.1. Response of DCS tuned using GA

For the proposed system, the MISO controllers tuned using the Genetic Algorithm produced a swift response with negligible overshoot and offset for the plant model in the simulation. As can be seen from the step response characteristics indicated in Table 2, in the simulation, the controlled system generated an output response where the process variables reached the settling band with no oscillations in all the operating regions. But in the real-time plant, the GA controller performed poorly in operating regions 2 and 3. Even though the controlled system generated response within the settling region quickly with no offset and negligible overshoot in operating region 1, in the operating regions 2 and 3, the response corresponding to conical tank C4200 was oscillating continuously and did not reach the desired settling band of ±10 % PV. The controlled system was only capable of generating a response that settled within ±23 % PV (approx.) and ±18 % PV (approx.) in operating regions 2 and 3. But this response of the GA controller pertaining to tank C4200 is better than the response generated from PSO and QFT controllers in operating regions 2 and 3. Meanwhile, the GA controller corresponding to conical tank C4100 fared well by generating a response that settled within the desired settling band with no overshoot and offset in all the operating regions. Figure 7 to Figure 9 depicts the system's response with the GA controller in the three operating regions.

7.2. Response of DCS tuned using PSO

Just as in the case of GA, the controllers tuned using the Particle Swarm Optimization algorithm also generated quick output response with negligible overshoot and offset for the plant model in simulation, as indicated in Table 2. Yet, the GA controller's response was better than the PSO controller in the operating region 3, with the former generating a much quicker response with slightly lower values of overshoot and offset. In the real-time plant with DCS, in operating region 1, the PSO based controller generated the most quicker control action, producing a response that settled within the desired band with no offset and little to no overshoot. Thus, the PSO based controller was found to be the most effective controller for this plant compared to its counterparts in operating region 1. But the performance of the controller is poor at higher setpoints. This can be inferred from the controller's time response characteristics corresponding to tank C4100 in operating regions 2 and 3, where the PSO controller generated responses with negligible offset and overshoot but with a much larger settling time than the GA controller. Moreover, even though the setpoint values corresponding to tank C4200 are lesser than tank C4100 in operating regions 2 and 3, the PSO controller's behavior is still worse in these regions, where the response was oscillating continuously and did not reach the desired settling band of ±10 % PV. The controlled system was only capable of generating a response that settled within ±30 % PV (approx.) and ±44 % PV (approx.) in operating regions 2 and 3. Thus, the performance of the PSO controller was found to be good in operating region 1. In contrast, in the other two operating regions, the PSO controller generated responses with the worst offset, and thus, the PSO controller was found to be not suitable in the higher operating ranges of the plant. The plant's response with PSO based controller in the three operating regions is depicted in Figure 10 to Figure 12.

7.3. Response of DCS tuned using QFT

The controller tuned using Quantitative Feedback Theory portrayed the ideal control action compared to other algorithms, in simulation, by generating the quickest responses with near-zero overshoot and offset in all the operating regions. But the performance of the controller in the real-time plant left a lot to be desired. Figure 13 to Figure 15 depicts the system's response with QFT based controller in the three operating regions. In the real-time plant with DCS, the QFT controller generated output response with quicker settling times than GA with negligible overshoot and offset in the operating region 1. Thus, the QFT controller's performance was second to PSO and was found to be better than the GA controller in the first operating region. In the case of operating regions 2 and 3, the QFT controller corresponding to tank C4100 generated a response with negligible overshoot and offset but with high settling times compared to PSO and GA controllers. Similarly, the controller corresponding to tank C4200 in operating regions 2 and 3 generated output response with high settling time and offset. Just as in the case of the other two algorithms, the output response was oscillating continuously and did not reach the desired settling band of ±10 % PV. The controlled system was only capable of generating a response that settled within ±23 % PV (approx.) and ±39 % PV (approx.) in operating regions 2 and 3. It should be noted that even though the response offset generated by the QFT controller in the second and third operating region is lesser than PSO, the characteristics of the control action are not better than GA either in these regions. Thus, the characteristics of the QFT based controller was found to be second best in all the operating regions and hence was not found to be suitable for implementation in the proposed nonlinear MIMO plant.

This disparity in the control action of the QFT-based controller in simulation and the real-time plant arises because, in simulation, the controller was tuned with QFT principles for setpoint tracking and input disturbance rejection for up to ±50 % uncertainty in the nominal transfer function coefficients. Since the coefficients of the transfer function are small for this proposed system, even ±100 % uncertainty may not be a massive deviation from the nominal transfer function and may not have much impact on the controller response in the simulation (Aparna,). But this unknown uncertainty in the mathematical model coefficients may impact the experiment unfavorably, leading to an insufficient control action from the QFT controller. This fact shall be explored further by analyzing the behavior of a similarly tuned QFT PI distributed controller in another nonlinear MIMO system with different operating characteristics.

Table 2: Time-Domain Characteristics of Plant Response

Case	Level	Characteristics	Simulation of plant model			Real-Time Plant with DCS		
			GA	PSO	QFT	GA (approx.)	PSO (approx.)	QFT (approx.)
1	G11-G21 Loop	Rise Time	1.401	1.052	0.380	25	25	20
		Settling Time	2.869	1.866	0.687	30	30	30
		Overshoot	0.040	0.016	0.010	0.167	0	0.167
		Offset	0.400	0.450	0.160	0	0	0
	G22-G12 Loop	Rise Time	0.468	0.689	0.254	25	30	40
		Settling Time	0.855	1.422	0.451	65	33	50
		Overshoot	0.012	0.048	0.053	0.1	0.3	0
		Offset	0.330	0.330	0.170	0	0	0
2	G11-G21 Loop	Rise Time	6.796	4.356	1.132	50	50	35
		Settling Time	12.566	7.626	2.017	80	100	120
		Overshoot	0.051	0.129	0.054	0.5	0.2	0.2
		Offset	0.800	0.680	0.170	0	0	0
	G22-G12 Loop	Rise Time	5.446	4.779	1.024	70	30	45
		Settling Time	9.763	8.866	1.842	80	40	110
		Overshoot	0.072	0.067	0.043	0.233	0.4167	0.25
		Offset	0.620	0.400	0.110	2.8	3.6	2.7
3	G11-G21 Loop	Rise Time	2.248	4.204	0.676	25	40	15
		Settling Time	4.012	7.503	1.209	30	50	110
		Overshoot	0	0.008	0	0	0.067	0.033
		Offset	0.490	0.900	0.150	0	0.6	0
	G22-G12 Loop	Rise Time	2.119	3.227	1.118	10	40	15
		Settling Time	3.870	6.078	2.020	20	50	35
		Overshoot	0	0	0	0.167	0.15	0.5
		Offset	0.090	0.150	0.050	3.2	8	7

Thus, from the experimental results, it is evident that, unlike in simulation, where all the control algorithms were capable of producing desired output response with negligible offset and overshoot (Aparna et al., 2018) irrespective of inherent uncertainties and interaction effect, in real-time, QFT fared better only with low interaction effect and lower values of tank level. From the time-domain characteristics of the plant output response, it can be seen that PSO produced the best response among the three algorithms for lower values of tank level, and GA generated a robust response with high as well as low interaction effect and thus was found to be suitable for mid and higher values of tank level exhibiting higher interaction effect. Accordingly, based on the above inferences, the DCS controller was tuned using PSO for lower tank levels, and GA was employed for higher tank levels, and the resulting output response is shown in the following Figure 16.

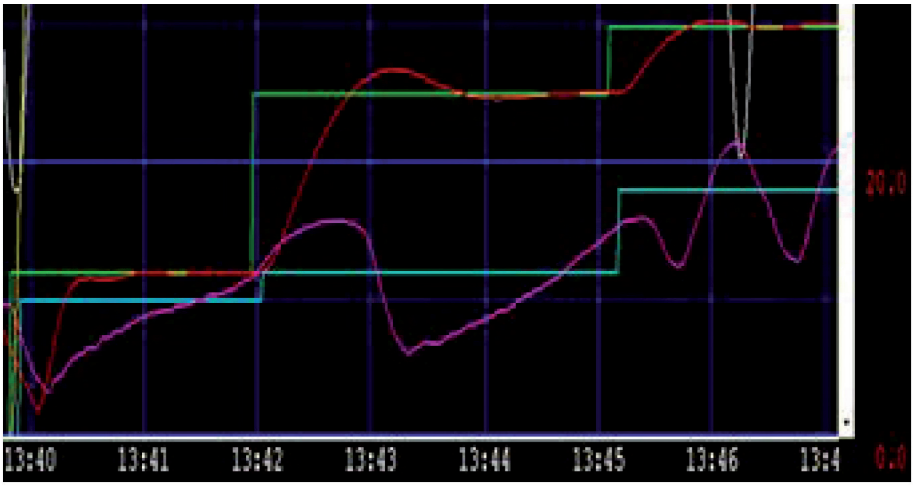

Figure 16: Response of DCS Controller tuned using PSO and GA

8. Limitations of the Research

According to the author's view, advanced control methods improve the overall versatility of traditional control strategies and solutions and contribute to superior conclusions. But it must be noted that the control methods described in this article, while proven appropriate for the specific plant, cannot be recommended for their use in different nonlinear MIMO plants in real-time. So, it would be most rational to assume that it is probably not yet possible to establish a comprehensive control strategy that can be used for all nonlinear MIMO plants. Therefore, a promising alternative to establishing a comprehensive control strategy is by revitalizing current control schemes by incorporating intelligence. Moreover, online implementation of other controller structures than PID may be explored instead of offline tuning, after due consideration of the limitations in the hardware and software technology in the proposed DCS system.

9. Conclusion

In this work, a multiloop PI level controller was implemented for a highly nonlinear interacting system using YOKOGAWA CENTUM CS 3000 DCS. The multiloop controller was tuned offline using robust and optimization algorithms like the Genetic Algorithm, Particle Swarm Optimization Algorithm, and Quantitative Feedback Theory. The offline gains were used to compute the gains of the PID controller for real-time implementation. The resulting experimental and simulation results were compared, and PSO and GA were found to produce better results in real-time than QFT with faster settling time and lesser overshoot and offset. Controller tuned using PSO performed excellently at lower tank levels. GA based DCS controller was found to be useful for mid and higher tank levels in the presence of considerable system interaction. But it can be seen from the results that there is some offset in the output response at higher tank levels. It is being considered that the inherent offset is due to the usage of Pneumatic-DPT instead of Capacitance-DPT for level measurement in this setup, which comprises a nonlinear tank structure.

9.1. Acknowledgments

The author is very much grateful to Ms. M. S. Murshitha Shajahan, Assistant Professor (Sr. Gr.), at B. S. Abdur Rahman Crescent Institute of Science and Technology, for her ideas and technical assistance.

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