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Nonlinear Model Predictive Control Strategy Based on Soft Computing Approaches and Real Time Implementation on a Coupled-Tank System

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Abstract — In order to effectively implement a good model based control strategy, the combination of different linear models working at various operating regions are mostly utilised since a single model that can operate in that fashion is always a difficult task to develop. This work presents the use of soft computing approaches such as evolutional algorithm called simulated annealing (SA), a genetic algorithm (GA) and an artificial neural network (ANN) to design both a robust single nonlinear dynamic ANN model derived from an experimental data driven system identification approach and a nonlinear model predictive control (NMPC) strategy. SA is employed to give an initial weight for the training of the ANN model structure while a gradient descent based Levenberg–Marquardt Algorithm (LMA) approach is used to optimise the ANN weights. The designed NMPC strategy is optimised using a stochastic GA optimisation method and is tested first in simulation and then implemented in real time practical experiment on a highly nonlinear single input single output (SISO) coupled tank system (CTS). An excellent control performance is reported over the conventional proportional-integral-derivative (PID) controller and results show the effectiveness of the approach under disturbances. The nonlinear neural network model proved very reliable in different operating regions. The SISO system can be upgraded to multi-input multi-output (MIMO) system while the whole NMPC approach can easily be adapted to other industrial processes.

Keywords— simulated annealing ; nonlinear model predictive control; artificial neural network; coupled tank system; genetic algorithm; levenberg–marquardt algorithm; real time implementation; single-input single-output

I. Introduction

Recent global advancement in technology had paved way for the popularity of process control in many industries. Complex processes in oil and gas production, oil refineries, and process plants are built from combinations of many smaller components such as the principles used in coupled tank system (CTS) (see figure 1). The understanding of the working mechanism of the CTS enhances the full grasp of the whole process. The concept of controlling a system is to make the physical plant behave according to certain stipulated constraints and specifications. Control of processes is very significant and invariably the cynosure of what goes on in these industries. An example of a common control problem in process industries is the control of fluid levels. A typical situation is the one that requires fluid to be supplied to a chemical reactor at a constant rate [1].

CTS are typical examples of some laboratory equipment that depict many complex processes. The various applications of CTS can be found in chemical blending, temperatures in storage tanks, hot-water inputs, temperature stabilisation and reaction vessels [1]. These functionalities of CTS equipment has provided an immense area of investigation for many researchers [2]. The coupled tanks apparatus are used to investigate basic and advanced control engineering principles which includes the study of static and dynamic systems [3]. Efficient and effective controls of these processes have immense economical advantage and its success depends on the type of control strategy [2]. However, there are control challenges that need to be met as there is a greater increase in productivity demands, higher efficiency, higher product quality specifications, tighter environmental regulations and demanding economic considerations [4], [5].

Model predictive control (MPC) is such an advance control strategy that can readily meet up with these challenges. In MPC, the manipulated variable is obtained by solving on-line an optimisation problem and the system model is used to predict the process outputs within the prediction horizon. MPC has been in use in the process industries such as chemical plants and oil refineries for the past decades and has now been extended its use to many other fields [6], [7]. MPC has had a significant impact in its application because of its ability to control and optimise complex processes with constraints [8]. Conventional controllers such as PID are not always able to provide good and acceptable results especially when system exhibit nonlinearity [9]. Model predictive controllers can apply use of either linear or nonlinear dynamic models of the process.

Many control strategies are often accomplished using linear techniques because linear models for controlling plants have been very well established [10] and invariably used in MPC strategies [6], [11], [12] over the past four decades [5].

The recent years have now witnessed a steady increasing attention in the area of NMPC [5] which has now drawn the attention of many control researchers. There is considerable amount of nonlinearity inherent in most chemical processes [13] and especially in CTS [14], [15] due to the basic dynamic equations, the characteristics of the valves and the because of the nonlinear flow characteristics in the tank. Most efficient process operations today require operating systems closer to the boundary of the admissible operating region [5] and therefore linear models are mostly insufficient to adequately represent the nonlinear dynamics of the plant [13]. Poor performance of linear MPC was further demonstrated by [16], [17]. However, a nonlinear control strategy and model might be invoked for classes of problems where the high degree of nonlinearity renders the linear techniques insufficient [10]. In view of this, a linear model cannot adequately cope with the nonlinearities of the CTS [14] . The task of obtaining a nonlinear model is usually rigorous and paralleled with the challenge to be able to operate in almost every regime unlike a linear model. These findings gave credence to much interest and promise nonlinear modelling which always comes with more computations and complexities. One of the major challenges with the use of nonlinear models is the difficulty in training procedure in order to obtain good model as it involves complex dynamics with complicated nonlinearities and unknown structure [16], [18]. The success of nonlinear models in control largely depends on the availability of a good nonlinear process models [16]. So many studies have confirmed the difficulties in training nonlinear models such as neural network and hence researchers tend to look for an alternate solution to training rather than venturing into the challenges of training difficulties. Such alternate solution could be to develop many models to operate at different operating points within the same process dynamics [15], [19] rather than using a single model. ANNs have been progressively used in many disciplines over the years. It has the capabilities of using past memories and experiences to generalise and adapt itself accordingly in order for modelling purposes [20]. Since It has been shown that a single model cannot properly represent the complete operating range of a dynamic system [19], the training of such nonlinear and non-convex problem is complex [21]. The optimisation of such problems requires a global optimisation method such as simulated annealing [22]. Degraded performance are often the results of much assumptions made during the development of the models [20] and therefore, a system identification approach is adopted in this work because the real experimental data gives the real situation of CTS dynamic without much assumptions.

The main focus of this paper is to first use a data driven system identification approach to develop a single dynamic nonlinear SISO feed forward ANN model of CTS that can operate in nearly all regions of operating points and also capable of handling rejecting disturbance by taking the advantages of the salient features of both LMA and simulated annealing for the weights optimisation during training. In addition, a NMPC strategy is further designed and tested first in simulation and then a real time practical implementation on a second order CTS. An excellent control performance is reported in this novel approach which is superior to the conventional PID controller.

II. DESCRIPTION OF THE COUPLED TWO-TANK SYSTEM

Liquid level control is probably the most common control problem in practical process systems [23]. The picture from the real time experiment practical setup at the control laboratory of Plymouth University is given in figure 1. The real time implementation is performed on CE105MV multi-variable coupled tanks apparatus from TQ TecQuipment (see figure 1).

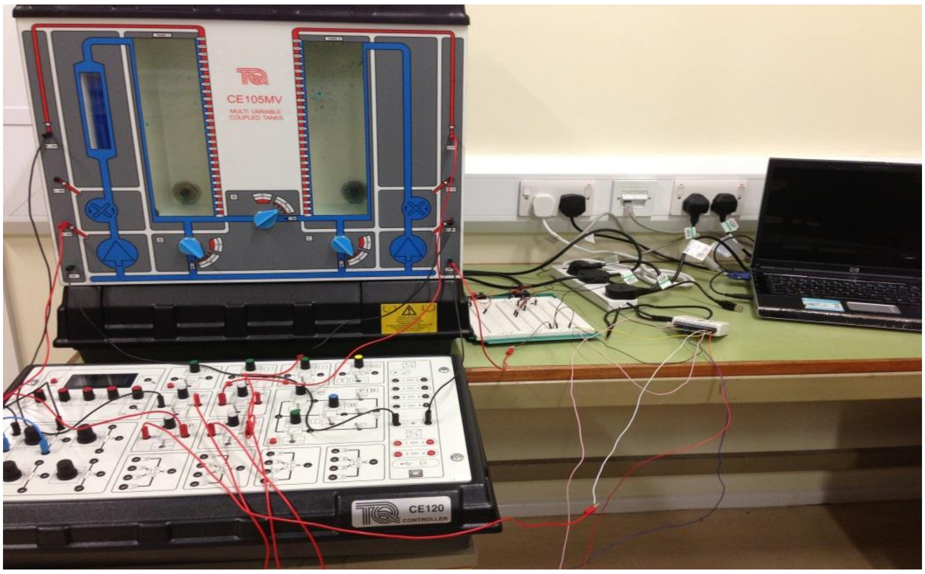

Fig. 1 Coupled tank setup at Plymouth University

Data acquisition (DAQ) device (NI 6009) from National Instrument with LabView® software driver is configured to acquire real time sensor data and to send the multivariable input to control the fluid levels in the tank. The 14-Bit DAQ is only capable of handling voltages in the range of 0 to 5 volts whereas pumps input voltage ranges between 0 and 10 volts. A Pentium *IV* computer with central processing unit (CPU) of *2.80 GHz* and *3.0 GB* of random-access memory (RAM) was used as an interface with the other equipment. The CE105MV unit comprises of two variable speed pumps, two tanks connected by a variable area channel and drain valves to a sump located in the base of the equipment. There are two calibrated piezo-resistive silicon pressure type depth transducer (level sensors), an electronic flow meter and a variable area gap flow meter to provide visual indication of flow rate. The control strategy is designed in a way that the rate of change of the control input is controlled in small steps to avoid major fluctuations.

The piece of equipment is called TQ CE105MV and there are different configurations that could be produced depending on the kind of experiment to be performed. There can be MIMO, SISO, single-input, multi-output (SIMO) or multi-input, single-output (MISO) configurations depending on the type of system to be investigated. This can be achieved by the manipulation of pumps inputs and by varying the sectional area of rotary valves A and C as shown in figure 2. The configuration adopted for this work is SISO with only pump #1 supplying voltage and pumping fluid into the left tank with valve A fully opened so that there can be an inflow also into the right tank while valve C is opened in midway position. The voltage input is also referred to as manipulated variable while the output which is the height or level of the fluid in the right tank is known as the controlled variable. At any given time, the height of the fluid in tank two (right hand tank), which is to be controlled is related to the water inlet rate and outlet rate. The dynamic equations (1) and (2) was derived using the first principles mass balance of flows equation on the tanks which is based on figure 2 and whereas equation (3) gives the nonlinear characteristics equation of the fluid leaving either of the tanks.

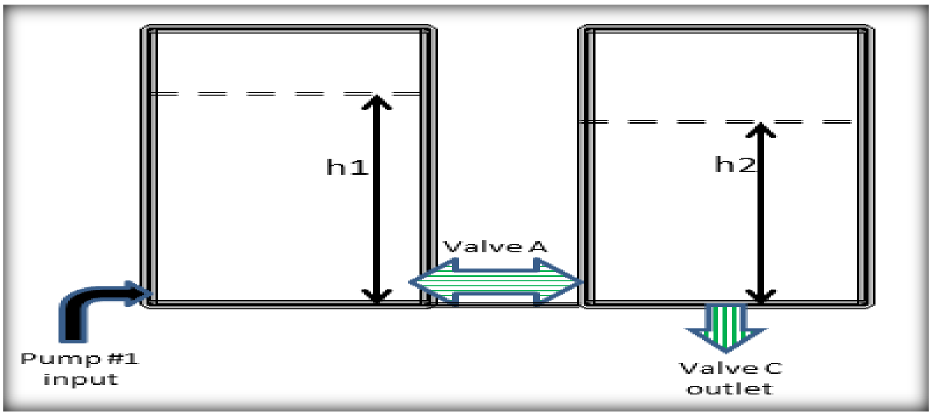

Fig. 2 Schematic layout diagram of SISO two-tank setup

$$A_1 \frac{dh_1}{dt} = K_1 V_1(t) \pm \beta_{12}\alpha_{12}\sqrt{\left(2g\left(h_1(t) - h_2(t)\right)\right)} \quad (1)$$

$$A_2 \frac{dh_2}{dt} = -\beta_2\alpha_2\sqrt{2gh_2} \pm \beta_{12}\alpha_{12}\sqrt{\left(2g\left(h_1(t) - h_2(t)\right)\right)} \quad (2)$$

$$Q_x = C_{cd}\beta_{xx}\alpha_x\sqrt{2gh_x} \quad (3)$$

In this work, subscripts 1 and 2 refer to tanks 1 and 2 respectively. A is the cross sectional area of the two tanks, α is the cross sectional area of the small outlet orifice, V is the voltage of the pump, h is the height of the liquid in the tank, β is the valve ratio of tanks, g is the gravitational constant, K is the pump gain and Q is the rate of flow of fluid out of the tanks. The Constant C_{cd} in equation 3 is called the discharge coefficient of the valve. This coefficient takes into account all fluid characteristics, losses and irregularities in the system such that the two sides of the equation balance and cancel out. The physical parameters of the TQ CE105MV coupled tank apparatus are given in Table 1.

TABLE I

physical parameter of coupled tank apparatus

System Parameter of the Coupled Tank Apparatus		
Symbol	**Quantity**	**Value**
Tank 1 & Tank 2	Tank cross sectional area	9.350×10^{-6} m^2
Valves A (α_{12}) and C (α_2)	Valve orifice cross sectional area	78.50×10^{-6} m^2
β_{12}	Discharge coefficient of 10mm valve orifice between tank 1 and tank 2	1.0
β_2	Discharge coefficient of valve C orifice	0.4123
g	Gravitational constant	9.80 m/s^2
Liquid Level Sensors	0 to 10V DC Output (0 to 250mm maximum tank height)	
Pump Flow Sensors	0 to 10V DC Output (0 to 4400cm^3/min)	

III. SYSTEM IDENTIFICATION

In order to derive a model for the plant, system identification is performed. Good model representation is important for the success of any control strategy. One of the most significant aspects of system identification is the data collection and one of the most laborious tasks is the training of the data in order to obtain a reliable model of the plant. The data gives the characteristics and the dynamic behaviour of the system and care must be taken to capture the salient and important features during the data collection procedure. So many approaches can be employed for the data collection process. The input signal used in this case is a uniformly distributed signal with combination of different amplitudes and frequencies so as to properly excite the plant. An experiment was performed to determine the sampling time and this ensures that the sampling frequency is greater than twice the maximum frequency of the signal to be sampled. The training of neural network structures requires the use of dynamic data rather than static data so that the past input and output data memory can be used to enhance the training effectiveness. Training must also be done to ensure less complexities and less computation and as the same time making sure that the trained model is accurate enough for prediction purposes. The choices of the number of hidden neurons and input-output delays determine the number of weights to be trained and hence the complexities of the neural network structure (see figures 3). During experiments, noise is undesirable and must be removed if there exist so as not to hamper the quality of the data to be trained.

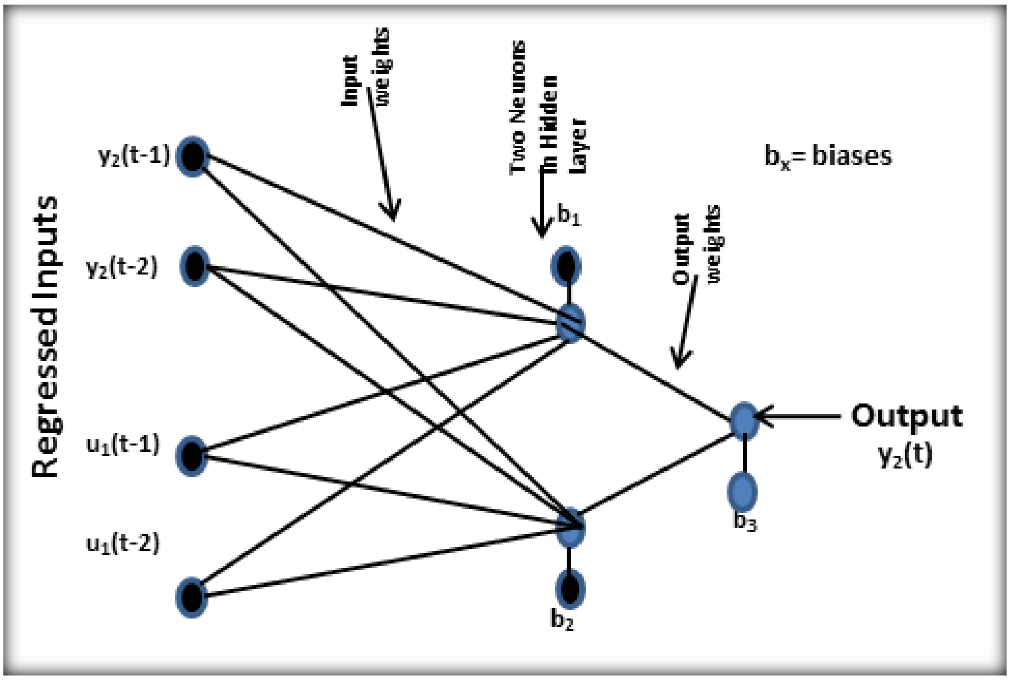

Fig. 3 Structure of a conventional SISO ANN

A. Data Collection

Three sets of different input-output data of 2980 sample each were collected from real open loop practical experiments on the SISO coupled tank system with a sampling rate (*Ts*) of 0.2 seconds with valve A fully opened and valve C in midway position while considering the system parameters and limits into consideration. The 2980 sample of data was collected within a period of 596 seconds which is less than 10 minutes. The samples were taken in such a way to show both the fluid filling up and draining process as this are parts of the crucial plant details. The reasons for collecting different sets rather than dividing a particular set into three parts are to ensure generalisation and prevention of overfitting. The efficacy of derived model is determined not by its performance on the training data but by its ability to perform well on other unseen data (testing data sets). The collected samples details and features are tabulated in table 2.

TABLE 2
THE RAW INPUT AND OUTPUT DATA DETAILS

Performance Function (Inputs)	Data One (Training)	Data Two (Validation)	Data Three (Testing)
Mean (volts)	5.1935	4.9423	5.0259
Variance (volts)	10.9190	10.7215	10.3617

The output of the three data sets: training, validating and testing collected from the coupled tank SISO systems are shown in figures 4 (a - c) respectively. Data set one were used to form the regressed input and output into the neural network training. Data set two were used for constant validation during the training process while data sets three were used for testing after the training was completed.

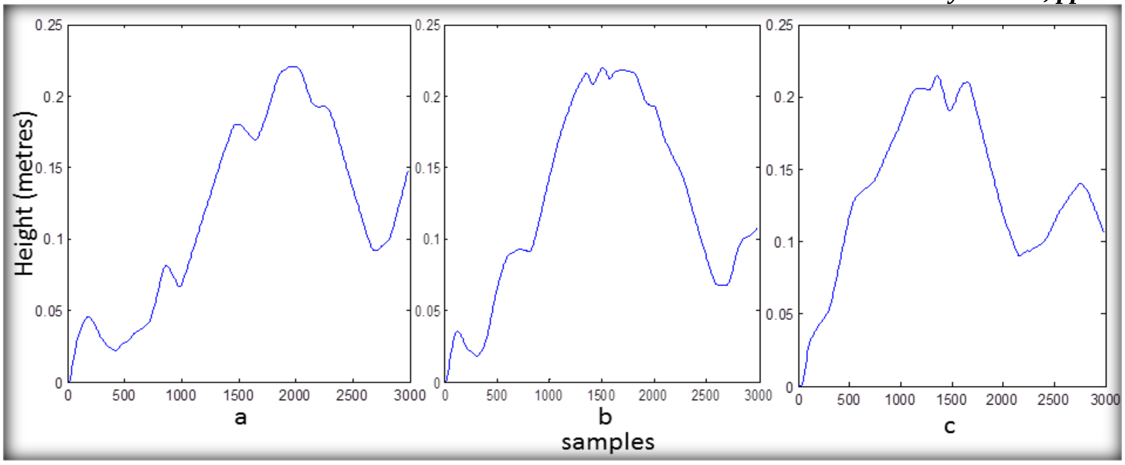

Fig. 4 Raw sampled output data sets

B. ANN Training Process

The structure for the ANN training is already given in figure 3. This structure has bias weight term vectors in both hidden and the output layer. These weights are usually initialised randomly using no prior information and which invariably increases the offline training computation time. An initial trial and error computation is carried out to determine the optimal number of two neurons in the hidden layer and two delays in both input and output in order to decrease the overall computation time. There are a total of 13 weights including the biases for 2 delays and 2 neurons structure as shown in figure 3.

For a SISO system, the input signal vector: $u_1(t)$ is the voltage applied to pump #1 which generates an inflow into both tanks while outputs $y_1(t)$ and $y_2(t)$ are the heights of the fluid in the tanks but $y_2(t)$ is the height level that needs to be controlled. The structure for the ANN with two neurons, 2 delays and giving a total of four regressed inputs which are: [$u_1(t-2)$, $u_1(t-1)$, $y_2(t-2)$ and $y_2(t-1)$] as shown in figure 3. ANN training is carried out in two stages. In order to reduce the training time, a simulated annealing [21], [22], [24] was used for initial search for weights to ensure that a local minimum solution could be avoided and to provide a good initial weight for the LMA algorithm to minimise the error between the trained output and target output, which subsequently leads to weights and biases update during computations. The performance index is calculated by using mean square error (MSE). The training process constantly validates the result with data sets two to ensure good correlation. Hyperbolic tangent activation function is used in hidden and linear activation function in the output layer. The activation function can have any value between plus and minus infinity, and squashes the output into the range -1 to 1. The training process is accomplished by making comparisons between the target output and the neural network output. The performance criterion is MSE. The weights are updated every iteration till the error is reduced to a considerably level and the network training stopping criteria are set to either when the MSE is less than $1.0e^{-7}$ or when the maximum numbers of iterations reach 500.

The system identification results show that model produced a low error difference between the target and the network output for all data sets. The training performance indexes values are shown in table 3. The low value of MSE error (excellent prediction qualities) also gives an indication of the system stability and training accuracy especially with unseen data sets. This quality is good for process control purposes.

TABLE 3

THE TRAINING PERFORMANCE RESULT FOR RAW INPUT OUTPUT DATA

Performance Function	**Data One (Training)**	**Data Two (Validation)**	**Data Three (Testing)**
MSE (m^2)	$6.4899e^{-9}$	$6.9932e^{-9}$	$7.1008e^{-9}$

IV. MODEL PREDICTIVE CONTROL STRATEGY

Controlling a plant is a lot more challenging task than what most engineers perceive. Model Predictive Control (MPC) is a form of an advanced control strategy in which the current manipulated control input applied to the real plant. A finite prediction horizon open-loop optimal control problem is derived by obtaining a real time solution online at each sampling instant. The optimisation yields an optimal control sequence and the first control in this sequence is applied to the plant. A model predictive control strategy was implemented by using a GA as the optimisation approach while the predictor is the nonlinear artificial neural network model. The schematic picture of the process is given in figure 5. The predictor's task is to predict the plant's outputs based on the regressed inputs at every instant. This is done for different control moves within a prediction range. The value of the control horizon should always be less than the prediction horizon. Genetic algorithm is used to solve and minimise the complex optimisation cost function (see equation 4) at every sampling time to determine the best optimum control inputs that give the least error between the predicted output and the trajectories reference signals and minimise the controller efforts. The first terms in equation 4 represents the error in prediction value and the reference valve while the second term denotes the change in the previous and the present control effort. In order to deal with real-time implementation constraints, termination measures were implemented to abort the optimisation once a defined sampling time is passed. This might invariably lead to convergence to some sub-optimal solution within the sampling time period.

$$\left\{\sum_{i=1}^{p}\left(\sum_{j=1}^{n_y}|w_{i+1,j}^{y}\left(y_j(k+i+1|k)\right)-r_j(k+i+1)|^2+\sum_{j=1}^{n_u}|\,w_{i,j}^{\Delta u}\Delta u_j(k+i|k)|^2\right)\right\} \quad (4)$$

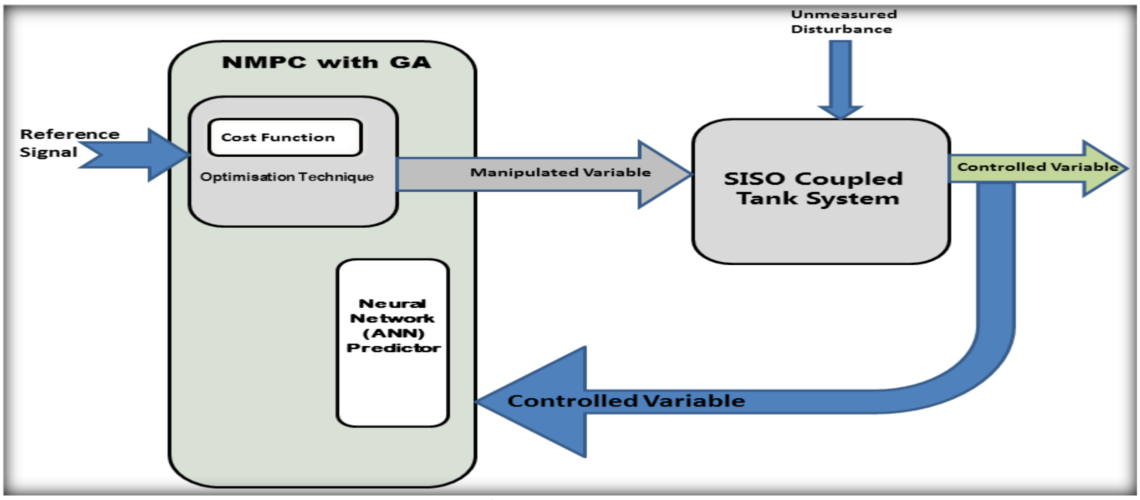

Fig. 5 Structure of SISO NMPC with GA Optimisation

Mutation brings variations, diversities and changes in the genetic structures of the overall population while crossover process interchanges the genetic structure of two or more chromosomes. The NMPC algorithm works in such a way that during the optimisation process, the best pairs of control horizon vector (population) is constantly retained so that the best population is not destroyed. Since the best population is constantly preserved, the maximum probability of crossover and mutation probabilities were chosen after a few trials. Two performance indexes are considered here to evaluate the performance of the NMPC strategy: the mean square error (MSE) and the average control energy (ACE). The mean square error is the addition of all the squares of the error differences between the reference and the plant output for the two outputs divided by the total number of samples. This is expressed in equation (5).

$$MSE = \frac{\sum_{j=1}^{N}(y_2^r - y_2^p)^2}{N} \quad (5)$$

In equation (5), superscripts r and p stand for reference value and plant output respectively while N stands for the total number of samples. The average control energy is defined as the addition of the squares of all the manipulated variables input to the plant divided by the total number of samples and expressed as:

$$ACE = \frac{\sum_{j=1}^{N} u_1^2}{N} \quad (6)$$

The trained ANN model of the CTS (SISO coupled tank system block in NMPC) in figure 5 is used as nonlinear prediction models with NMPC as the control strategy. The CTS is designed in SIMULINK® (see figure 6) using the fundamental equations expressed in equations (1-3) was used to simulate the real plant.

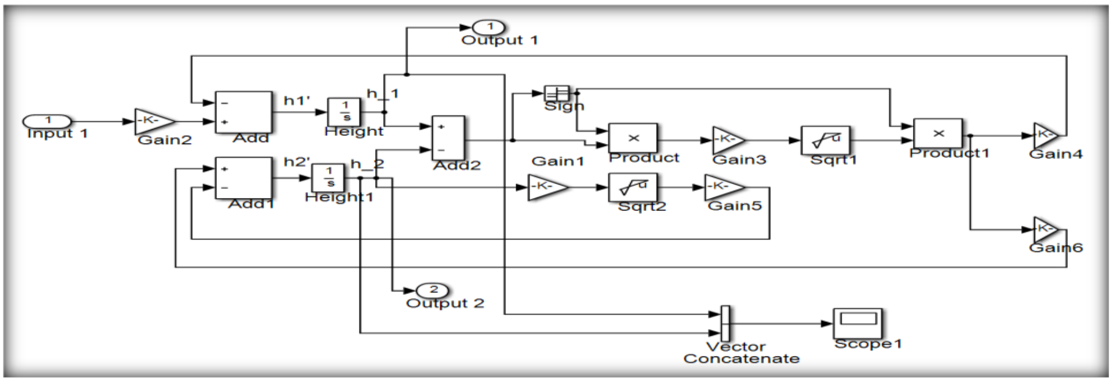

Fig. 6 SISO coupled tank system in SIMULINK® design

Both PID and NMPC strategies were designed primarily to control the height in tank #2 with while monitoring the level in tank #1 to prevent an overflow which is not desirable in practical applications. PID controller is manually tunned and optimised to give the best performance. Various parameters were initially used for the optimal optimisation in the NMPC strategy. After the initial trial and error, the optimal parameters that produce results within sampling interval were selected as follows: population size of 20, prediction horizon of 5, and control horizon of 2, generation number of 4, and crossover ratio of 0.5 and mutation ratio of 0.5. The results of implementing both controllers in simulation at different operating regions are tabulated in table 4 using the SIMULINK® model of figure 6. The MSE and the ACE values were obtained for the control strategies at 5 different operating points: 19cm, 15cm, 10cm, 5cm and 1cm are presented for 4000 samples each.

TABLE 4

COMPARISON BETWEEN PID AND ANN-NMPC STRATEGY WORKING AT DIFFERENT OPERATING REGIONS

	PID	**NMPC**	**PID**	**NMPC**	**PID**	**NMPC**	**PID**	**NMPC**	**PID**	**NMPC**
Level	**19cm**		**15cm**		**10cm**		**5cm**		**1cm**	
MSE(m^2)	$1.2e^{-3}$	$1.0e^{-3}$	$6.73e^{-4}$	$4.32e^{-4}$	$3.25e^{-4}$	$1.25e^{-4}$	$1.03e^{-4}$	$1.78e^{-5}$	$1.00e^{-5}$	$4.63e^{-7}$
ACE(v^2)	40.75	49.70	29.27	40.22	18.58	28.56	8.68	16.82	1.46	4.85
ELP(s)	80.07	239.55	78.36	237.25	78.48	237.53	78.68	242.30	78.88	242.06

Both PID and NMPC strategy exhibits a good set point and efficient control tracking at different operating regions but the results of the NMPC strategy is more superior to the PID strategy. PID strategies took a long time to arrive at a steady state and this is not desirable (see figure 7). This result shows that the ANN model can effectively operate in all regions without employing series of cascade models. The NMPC strategies have fast responses and no steady state errors. However, PID controller will have to be manually retuned to be able to work effectively in a particular regime.

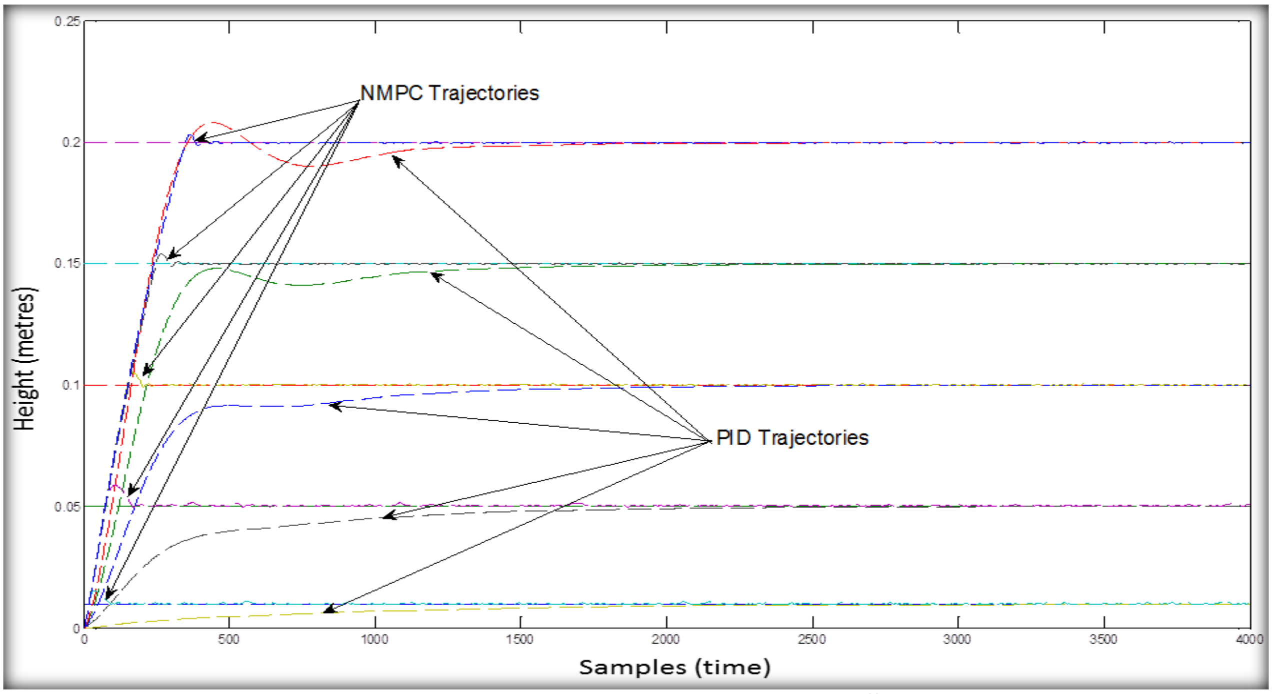

Fig. 7 Comparison between PID and ANN-NMPC strategies working at different operating regions

NMPC strategies have a smaller MSE values for all operating points as compared to the PID strategy (see table 4). Furthermore, the results of figure 7 and table 4 show that both the ACE and elapsed time for PID are smaller than that of NMPC strategy. This is due to the fact that PID has a very smooth controller action and the optimisations process of PID strategy does not involve much computation unlike the GA in NMPC. The PID controller and the actuator will have to do less work to be able to effectively control the CTS unlike the NMPC strategy. Similarly, figure 8(a) shows that graph of the simulation comparison in the responses of both controllers tracking the set point 10cm level of the CTS while figure 8(b) shows their controller actions for 1000 samples. The NMPC controller has a fast rise time unlike the PID and this is attributed to the effective optimisation process of the manipulated variable by GA in the NMPC strategy. The MSE and ACE values for the simulations are shown in table 5.

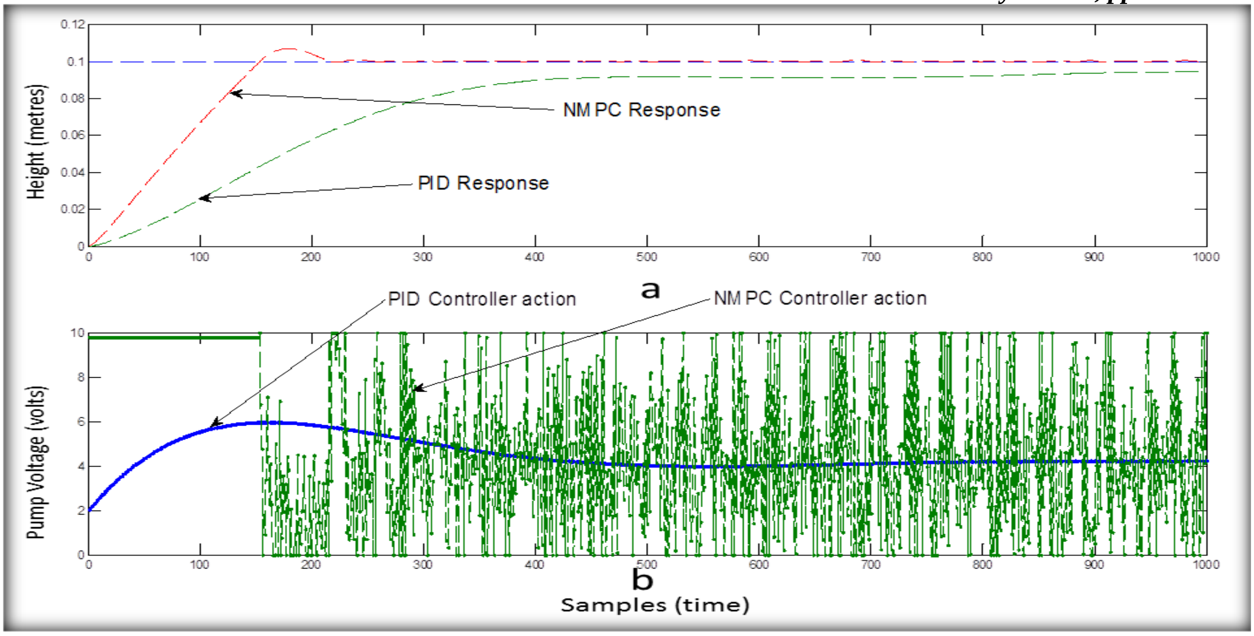

Fig. 8 Simulation: (a) plant responses (b) controller actions of both PID and ANN-NMPC strategies tracking 10 cm level

A real time practical control implementation is performed using NI 6009 DAQ wired directly to the CTS to acquire and send online real data. Figure 9(a) shows that graph of the real time implementation comparison in the responses of both controllers tracking the set point 10cm level of the CTS while figure 9(b) shows their controller actions for 1000 samples. The figures (8-9) and the values in table 5 give the comparison and show that the simulation results are better (smaller MSE and ACE) than the real time results for both controllers. This is due to errors in the physical system parameters, valve positions, sensors reading and analogue amplifiers outputs. The PID real time result has time inherent delays which further make NMPC results more superior.

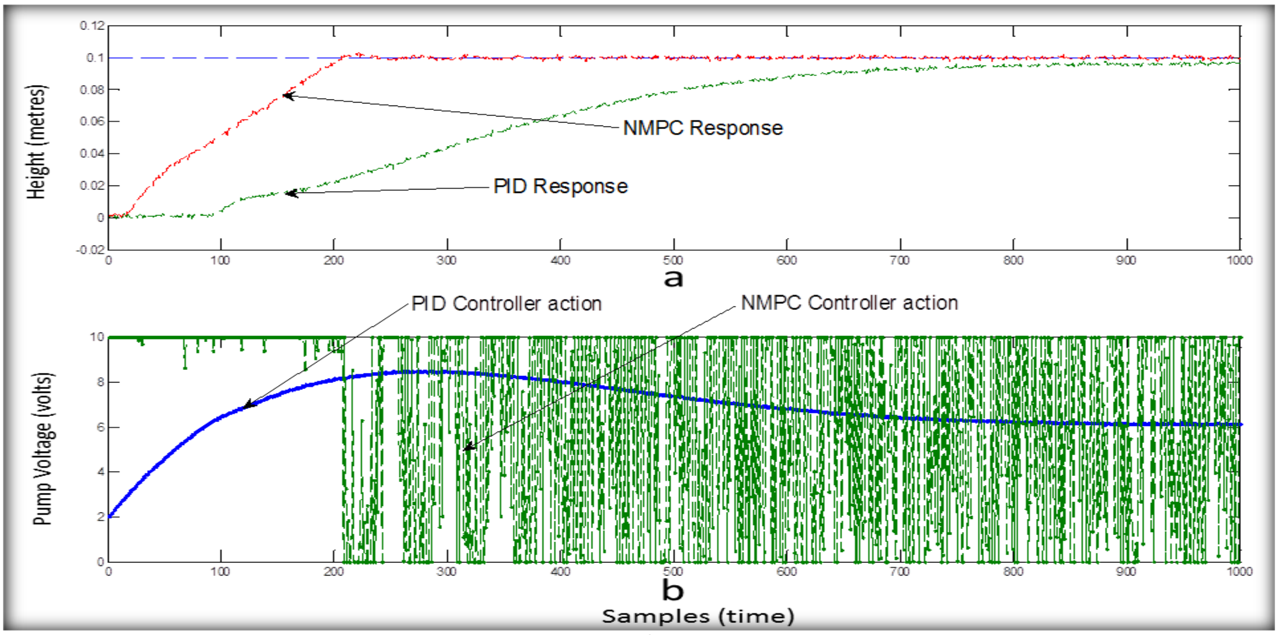

Fig. 9 Real time: (a) plant responses (b) controller actions of both PID and ANN-NMPC strategies tracking 10 cm level

The practical experiment shown in figure 9 is repeated in figure 10 but with disturbance signal introduced through the idle pump #2 for 10 samples after midway through the experiment while valve C is also slightly altered to change the dynamics of the CTS. Most model based control strategies might not perform well in presence of disturbance due to the fact that online predictions are based on offline models. Results show that both controllers are able to reject the disturbance effectively. This further buttress shows the adaptive robustness and stability of ANN-NMPC strategy. Figure 10(a) shows that graph of the real time implementation with disturbance rejection comparison in the responses of both controllers tracking the set point 10cm level of the CTS while figure 10(b) shows their controller actions for 1000 samples. The NMPC MSE value for the real time disturbance rejection results ($4.91e^{-4}$ m^2) is much better than without rejection ($6.53e^{-4}$ m^2) but it took more elapsed time. The same goes for ACE and the PID cases. The comparison results between simulation, real time and disturbance rejection are shown in table 5.

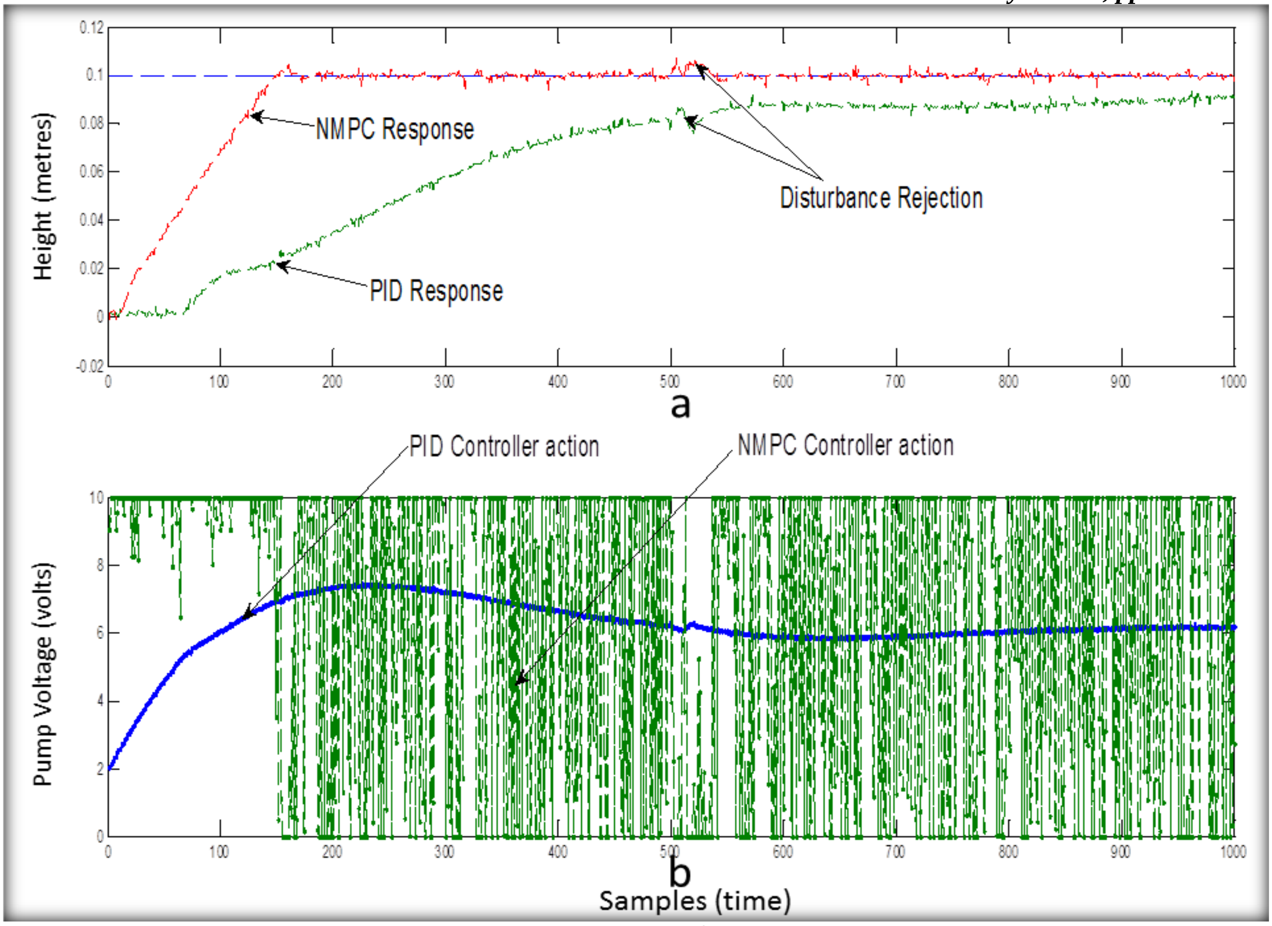

Fig. 10 Real time disturbance: (a) plant responses (b) controller actions of both PID and ANN-NMPC strategies tracking 10 cm level

TABLE 5
COMPARISON BETWEEN SIMULATION, REAL TIME AND DISTURBANCE REJECTION FOR THE CONTROL STRATEGIES

	PID CONTROLLER			NMPC STRATEGY		
Action	**Simulation**	**Real Time**	**Disturbance Rejection**	**Simulation**	**Real Time**	**Disturbance Rejection**
MSE(m^2)	$1.30e^{-3}$	$2.50e^{-3}$	$2.00e^{-3}$	$5.07e^{-4}$	$6.53e^{-4}$	$4.91e^{-4}$
ACE(v^2)	20.68	48.31	39.25	37.46	60.32	58.06
ELP(s)	162.74	236.86	386.91	263.34	375.65	549.16

V. CONCLUSIONS

This work has demonstrated both in simulation and in real time implementation of ANN-NMPC strategy using GA for a SISO second order coupled tank system. In order to handle the difficulties in network training, a simulated annealing evolution algorithm is employed for initial network training to give an initial weight for the LMA algorithm. LMA can sufficiently prevent the training process from becoming trapped in a local minimum solution only if there is a good initial starting weight. The obtained reliable nonlinear model of the CTS showed the effectiveness of the system identification procedure which allows for a wide range of prediction capabilities. Results further showed that the single ANN model is well suitable to operate in all regions of operating points and the capabilities of handling disturbance rejection. This shows the strength of the ANN nonlinear model in handling difficult problems especially when properly trained. Furthermore, the NMPC strategy and GA optimization is efficient in trajectory set point tracking. The whole strategy is well suited for chemical processes with varying interaction rates. The NMPC strategy results show superior performance over the conventional PID controller. Further works will concentrate on improving ANN-MPC strategy to handle nonlinear MIMO CTS problems in real time.

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