Design of Conventional and Neural Network Based Controllers for a Single-Shaft Gas Turbine

Abstract

Purpose – The purpose of this paper is to develop and compare conventional and neural network based controllers for gas turbines.

Design/methodology/approach – Design of two different controllers is considered. These controllers consist of a NARMA-L2 which is an ANN-based nonlinear autoregressive moving average (NARMA) controller with feedback linearization, and a conventional proportional-integrator-derivative (PID) controller for a low-power aero gas turbine. They are briefly described and their parameters are adjusted and tuned in Simulink-MATLAB environment according to the requirement of the gas turbine system and the control objectives. For this purpose, Simulink and neural network based modelling is employed. Performances of the controllers are explored and compared on the base of design criteria and performance indices.

Findings – It is shown that NARMA-L2, as a neural network based controller, has a superior performance to the PID controller.

Practical implications – Using artificial intelligence in gas turbine control systems.

Originality/value – Providing a novel methodology for control of gas turbines.

Keywords: Gas turbine, neural network, control, PID, NARMA-L2.

Paper type Full Research Paper

Introduction

Control system is a vital part of any industrial equipment. Lacking a proper control system in gas turbines (GT) can lead to serious problems such as compressor surge, overheat, overspeed, etc (Giampaolo, 2009). The final effect of these problems may be system shutdown and severe damages to the main components of GTs. Modelling of control systems, before their implementation in real plants, is an efficient and cost-saving strategy in industrial applications. The need for controllers with high quality standards to reliably manipulate operations in complex industrial systems, such as gas turbines, has been increasing dramatically. These controllers should have the capability of dealing with restrictions on control strategies and internal variables (Suarez, Duarte-Mermoud, & Bassi, 2006). This necessity has led to development of different kinds of controllers which can be applied to industrial plants. Applications of gas turbine modelling to control systems can be categorized into white-box and black-box approaches.

White-Box Models

A white-box model is used when there is enough knowledge about physics of the system. In this case, mathematical equations regarding dynamics of the system are utilized to make a model. This kind of model deals with dynamic equations of the system which are usually coupled and nonlinear (Jelali & Kroll, 2004).

Significant research has been carried out in the field of white-box controllers. Ricketts (1997) showed that the dynamic model developed for a twin-shaft gas turbine by using a generic methodology and performance data sets, could represent an ideal application to adaptive control schemes. Ailer et al. ((2001), (2002), (2005)) carried out different research to design and develop control systems for a low-power gas turbine. Modifications in a heavy-duty power plant gas turbine control system were applied by Agüero et al. (2002) . Centeno et al. (2002) reviewed typical gas turbine dynamic models for power system stability studies. Ashikaga et al. (2003) carried out a study to apply nonlinear control to gas turbines. They reported two applications of nonlinear control. The first one was the starting control using the fuzzy control, and the other was the application of the optimizing method to variable stator vane (VSV) control. The objective was to increase thermal efficiency and to decrease nitrogen oxide emission. However, the algorithms for solving optimization problems were complicated, time-consuming and too large to be installed easily in computers.

Zaiet et al. (2006) proposed modelling and nonlinear control of a gas turbine based on the previous studies in the literature. They stated that their methodology could provide more flexibility in design of strategies, controlling the speed and surge simultaneously, and accelerating the compressor without stalling problems. A simple and fast linear model for real-time transient performance of a jet engine control was developed by Lichtsinder and levy (2006) . Pongraz et al. (2008) used an input-output linearization method to design an adaptive reference tracking controller for a low-power gas turbine model. Tong and Yu (2008) presented a dynamic model of a micro turbine and its nonlinear PID controller. A robust controller for an identified model of a power plant gas turbine was designed by Najimi and Ramezani (2012). The applied model was built on the basis of Rowen’s model (Rowen, 1992) and by using real data for tuning the GT parameters.

Kolmanovsky et al. (2012) developed a robust control system for aero gas turbines. To develop stable control architectures for gas turbine engines, Pakmehr et al. (2013) investigated a nonlinear physics-based dynamic model of a twin-shaft aero engine. There have also been remarkable research, trying to develop theoretical background of model predictive controllers (MPC). An overview of industrial MPC technology was presented by Qin et al. ((1997), (2003)). Richalet ((1978), (1993)) discussed industrial applications of MPC. A pedagogical overview of some of the most important developments in MPC theory, and their implications for the future of MPC theory and practice, was discussed by Nikolaou (2001). Rawlings (2000) provided a review of MPCs for tutorial purposes.

Black-Box Models

A black-box model is used when no or little information is available about physics of the system (Jelali & Kroll, 2004). In this case, the aim is to disclose the relations between variables of the system using the input and output data of the system. Artificial neural network (ANN) is one of the most significant methods in black-box modelling. They have shown a high capability in modelling and control of dynamic systems such as gas turbines. The neural network controllers are widely known for their excellent reference tracking capability and their flexibility for implementation on various systems. Although PID controllers are still being widely used in control loops in majority of industrial plants, their algorithm might be difficult to deal with in highly nonlinear and time-varying processes (Junghui & Tien-Chih, 2004). For these reasons, the learning-based control methodology such as neural network has been widely used in various industrial applications.

There is a strong motivation for development of a large number of schemes for ANN-based controllers due to their successful industrial applications (Agarwal, 1997). ANN-based models for control systems can be trained using the data generated from a previously simulated model of the plant, or can be obtained directly from special open loop experiments performed on the plant (Suarez, Duarte-Mermoud, & Bassi, 2006). It has been demonstrated that input-output data sets of system parameters, obtained from a plant which is controlled by a linear controller, can be reliably used for ANN training process (Draeger, Engell, & Ranke, 1995).

Remarkable efforts have been done during recent decades to use neural network based controllers (Neurocontrol) for industrial systems. A survey in some reputable scientific databases shows that the number of papers in the field of neurocontrol has been increased significantly from 1990 to 2008 (Efe, 2011). Agarwal (1997) presented a systematic classification of various neurocontrols and showed that the neurocontrol studies are essentially different despite all their similarities. Hunt et al. (1992) and Balakrishnan & weil (1996) also carried out a literature survey in this area in 1992 and 1996 respectively. Rowen and Housen (1983) investigated GT airflow control for optimum heat recovery and its advantages at gas turbine part-load conditions. Hagan et al. ((2002), (1999)) presented an overview of neural networks and their applications to control systems.

Practical use of ANN to control complex and nonlinear systems was explored by Nabney and Cressy (1996). Another effort was carried out by Dodd and Martin (1997), more or less with the same objectives. They proposed an ANN-based adaptive technique to model and control an aero gas turbine engine and to maintain thrust at a desired level while minimizing fuel consumption in the engine. Psaltis et al. (1988) employed a multi-layer neural network processor and used different learning architectures to train the neural controller for a given plant. Lietzau and Kreiner ((2001), (2004)) investigated possible applications of model-based control concepts for jet engines. To improve the transient stability performance of a power system, Dash et al. (2000) presented a radial basis function neural network (RBFNN) controller with both single and multi neuron architecture for the unified power flow controller (UPFC).

Development of an intelligent optimal control system with learning generalization capabilities was explored by Becerikli et al. (2003). They used a DNN as a control trajectory priming system to overcome the non-dynamic nature of popular ANN architectures. The trained DNN helped to generate the initial control policy close to the optimal result. Litt et al. (2003) explored an adaptive, multi-variable controller for deterioration compensation of the thrust due to aging in an aero engine gas turbine. They used the relationship between the level of engine degradation and the overshoot in engine temperature ratio, which was the cause of the thrust response variation, to adapt the controller. A mathematical model of a combined cycle gas turbine (CCGT), as part of a large-scale national power generation network, was developed by Lalor and O'Malley (2003). Junghui and Tien-Chih (2004) presented a new control approach by employing a PID controller and a linearized neural network model. Their research objective was to make a balance between nonlinear and conventional linear control designs in order to improve the control performance for the nonlinear systems.

Some of the researchers tried to develop ANN-based MPC for control of processes. Sahin et al. (2005) proposed a neural network approach for a nonlinear model predictive control (NMPC). They showed that the MPC can be effectively employed to control nonlinear industrial processes without linearization requirement. Ławryńczuk ((2007), (2007)) discussed details of NMPC algorithms for MIMO processes modelled by means of neural networks of a feedforward structure. Jadlovská et al. (2008) presented classical and nonlinear autoregressive exogenous (NARX) approaches to design generalized predictive control (GPC) algorithm for a nonlinear system. They concluded that the intelligent neural GPC controller, which used linearization techniques, showed tremendous advantages over the conventional nonlinear predictive controller. Suarez et al. (2006) developed a new predictive control scheme based on neural networks to linearize nonlinear dynamical systems. Cipriano (2006) discussed implementation of fuzzy predictive control for power plants using nonlinear models based on fuzzy expert systems, and using fuzzy logic to characterize the objective function and the constraints. A nonlinear model predictive controller (NMPC) for frequency and temperature control of a heavy-duty industrial power plant gas turbine (IPGT) was developed by Kim et al. (2013). They showed that the proposed control system has superior performance to PID control in terms of responses to disturbances in electrical loads. Ghorbani et al. ((2008), (2008)) and Mu & Rees (2004) explored applications of ANN-based MPC to gas turbines. Mu and Rees (2004) investigated nonlinear modelling and control of a Rolls Royce Spey aircraft gas turbine. They used neural networks to indentify the engine dynamics under different operational conditions. The researches applied an approximate model predictive control (AMPC) to control shaft rotational speed. The results proved that the performance of AMPC as a global nonlinear controller was much better than the gain-scheduling PID controllers. AMPC showed optimal performance for both small and large random step changes as well as against disturbances and model mismatch. In another effort, Mu et al. (2005) examined two different approaches to design a global nonlinear controller for an aircraft gas turbine. They compared and discussed the properties of AMPC and NMPC. The results showed that both controllers provided good performance for the whole operational range. However, AMPC showed better performance against disturbances and uncertainties. Besides, AMPC could be gained analytically, required less computational time and avoided local minima.

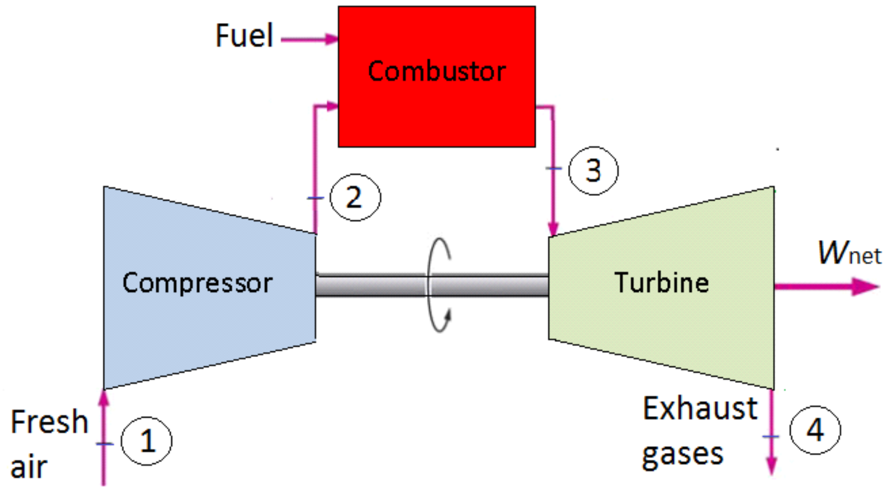
Sisworahardjo et al. (2008) presented a neural network controller for power plant micro gas turbines (MGT). They applied both proportional-integrator (PI) and ANN controllers to control voltage, speed, temperature and power. Yamagami et al. (2008) developed an optimal control system for the gas turbines as a result of development of the control systems for the entire of a power plant including steam turbines, waste heat recovery boilers, and auxiliary machines. Implementation of a MPC on a heavy-duty power plant gas turbine was investigated by Ghorbani et al. ((2008), (2008)). They built a model of the system based on a mathematical procedure and the 'autoregressive with exogenous input (ARX) identification method. The research objective was to design a controller that could adjust rotational speed of the shaft and exhaust gas temperature by the fuel flow rate and the position of inlet guide vanes (IGV). The MPC controller showed superior performance to both PID controller and SpeedTronic control system. Using PID and ANN controllers for a heavy-duty gas turbine plant was investigated by Balamurugan et al. (2008). They applied Ziegler-Nichols method to tune PID controller parameters. Besides, they trained an ANN controller using backpropagation method to control the speed of the gas turbine. The simulation results showed that the ANN controller performed better than the PID one. Bazazzadeh et al. (2011) developed a mathematical model of a controller for an aero gas turbine by using fuzzy logic and neural network methods in Simulink-MATLAB environment. The neural networks were employed as an effective method to define the optimum fuzzy fuel functions. The resulting controller could successfully achieve the desired performance and stability.

Because of nonlinear nature of industrial systems and deviation of control systems from design objectives, there are still high demands for controllers and control approaches which can incorporate system nonlinearity. Different control strategies and a variety of controllers can be employed and tested on gas turbine models before implementation on real systems. In this paper, the structures of a conventional PID controller and a NARMA-L2 which is an ANN-based controller are briefly described. The relevant parameters are set up according to the requirements of the controller design for the Simulink model of a low-power gas turbine; already developed based on thermodynamic equations and energy balance (Ailer, Santa, Szederkenyi, & Hangos, 2002). A comparison is made between the performances of these controllers and concluding remarks are discussed. The main motivation for this research is to investigate the capability of ANN-based controllers in small industrial gas turbines, such as aero gas turbines, within desired limits of performance. The first contribution of this study is development and comparison of a black-box and a white-box controller on industrial gas turbines. The second and main contribution of the paper is to demonstrate that the ANN-based controller has a superior performance on gas turbines compared to the PID one. Besides, the methodology employed for simulation of the ANN-based controller, for the first time used for gas turbines.

Gas Turbine Simulink Model

The data for this study was generated using a simulated nonlinear dynamic model of an aero single-shaft gas turbine. Figure 1 shows a typical single-shaft gas turbine and its main components including compressor, combustion chamber (combustor), and turbine.

Figure 1 Schematic of a typical single-shaft gas turbine.



The model has been already developed and verified for loop-shaping control purposes by Ailer et al. (2002) and for ANN-based modelling by Asgari et al. (2013). The model was developed and simulated in Simulink-MATLAB, on the base of engineering principles, gas turbine dynamics, constitutive algebraic equations, and by using operational data. Model verification was performed by open-loop simulations against qualitative operation experience and engineering intuition (Ailer, Santa, Szederkenyi, & Hangos, 2002). In this study, the Simulink model was rebuilt using the same principles and equations. Eqn (1), (2) and (3) are the main equations of the gas turbine employed in the Simulink model (Ailer, Santa, Szederkenyi, & Hangos, 2002). Definition of each of the parameters in these equations is provided in Table 1. $\dot{m}_{fuel}$, M_{load} , T_{01}, and P_{01} were considered as inputs of the model. The other GT parameters can be considered as outputs of the system (Asgari, Chen, Menhaj, & Sainudii, 2013). Figure 2 shows a simplified Simulink model of the gas turbine plant. In this figure, n and T_{04} are shown as the outputs of the system.

$$\frac{dm_{comb}}{dt} = \dot{m}_C + \dot{m}_{fuel} - \dot{m}_T \tag{1}$$

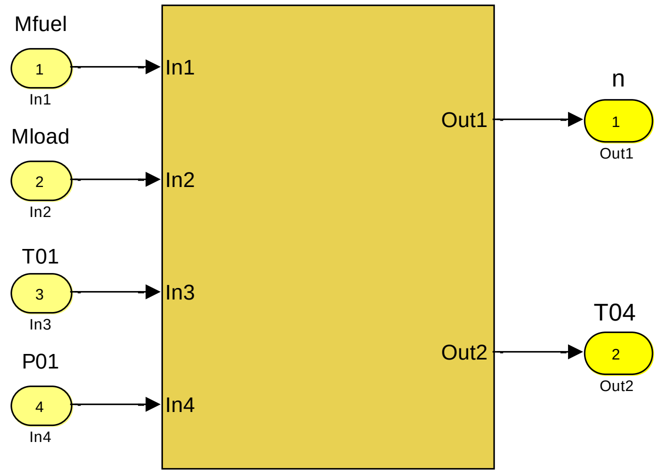
$$\frac{dP_{03}}{dt} = \frac{P_{03}}{m_{comb}}(\dot{m}_C + \dot{m}_{fuel} - \dot{m}_T) + \frac{P_{03}}{T_{03}\, C_{vmed}\, m_{comb}}(\dot{m}_c C_{p_{air}} T_{02} - \dot{m}_T C_{p_{gas}} T_{03} + Q_f \eta_{comb}\, \dot{m}_{fuel} - C_{vmed}\, T_{03}(\dot{m}_C + \dot{m}_{fuel} - \dot{m}_T)) \tag{2}$$

$$\frac{dn}{dt} = \frac{1}{4\pi^2 \Theta n}\left(\dot{m}_T C_{p_{gas}}(T_{03} - T_{04})\eta_{mech} - \dot{m}_c C_{p_{air}}(T_{02} - T_{01}) - 2\pi \frac{3}{50} n M_{load}\right) \tag{3}$$

Table 1 Definition of parameters

Parameter	Symbol	Unit
rotational speed (number of revlutions)	n	1/s
temperature at section 1	$T01$	K
temperature at section 2	$T02$	K
temperature at section 3	$T03$	K
Temperature at section 4	$T04$	K
pressure at section 1	$P01$	Pa
pressure at section 2	$P02$	Pa
pressure at section 3	$P03$	Pa
pressure at section 4	$P04$	Pa
air mass flow rate in compressor	$\dot{m}_C$	kg/s
gas mass flow rate in turbine	$\dot{m}_T$	kg/s
fuel mass flow rate	$\dot{m}_{fuel}$	kg/s
gas mass in combustion chamber	m_{comb}	kg
time	t	s
specific heat of air in constant pressure	$C_{P_{air}}$	J/kg K
specific heat of gas in constant pressure	$C_{P_{gas}}$	J/kg K
medium Specific heat in constant volume	$C_{v_{med}}$	J/kg K
fuel lower thermal value	Q_f	J/kg
combustion chamber efficiency	η_{comb}	-
mechanical efficiency	η_{mech}	-
inertial moment	Θ	$kg\ m^2$
moment of load	M_{load}	N m

Figure 2 Simplified Simulink model of the gas turbine.



Gas Turbine Control System

The gas turbine model described in prior section is used for the controller design in research. Figure 3 shows the closed-loop diagram of the control system for the GT model. It includes the plant which is the gas turbine system, the controller, random reference and indicator blocks. Fuel mass flow rate and rotational speed are considered as variable input and output of the plant respectively. Eqn (4) which is concluded from Eqn (1) and (3), shows the relation between the rotational speed and the fuel mass flow rate. The controller can be any of the controller structures including NARMA-L2 or PID, as will be discussed later in this paper. They are already implemented in MATLAB software and their parameters need to be tuned according to the plant specifications and control design requirements.

$$\frac{dn}{dt} = \frac{1}{4\pi^2 \ominus n}\left(\left(\frac{dm_{comb}}{dt} - \dot{m}_C - \dot{m}_{fuel}\right) C_{p_{gas}} (T_{03} - T_{04}) \eta_{mech} - (\frac{dm_{comb}}{dt} - \dot{m}_{fuel} + \dot{m}_T) C_{p_{air}} (T_{02} - T_{01}) - 2\pi \frac{3}{50} n M_{load}\right) \tag{4}$$

Figure 3 The closed-loop diagram of the control system for the gas turbine engine system.

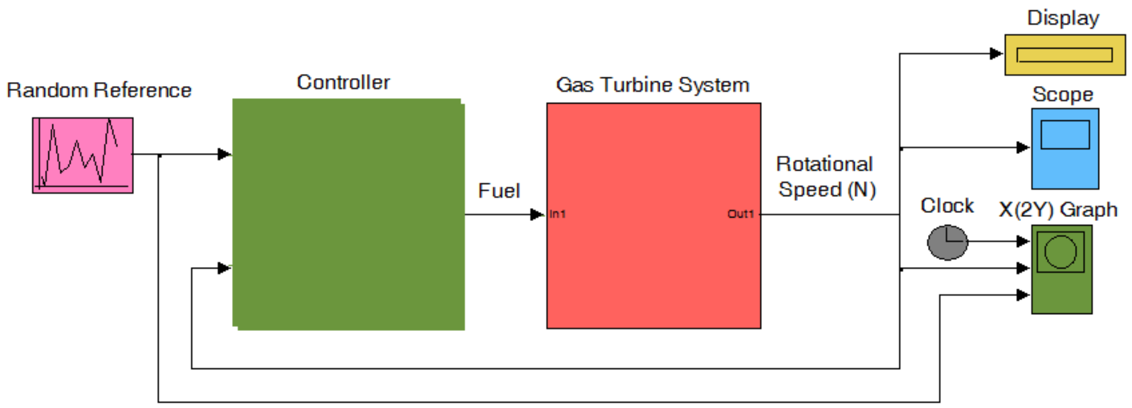


Figure 4 shows the adjusted parameters for random reference block diagram. The random reference is adjusted between 695 and 705 *rpm* with a sample time of 0.2 second. It produces random step signals based on the adjusted parameters. The goal is to evaluate the sensitivity of the designed controllers to fluctuations of rotational speed. Because the rotational speed of the gas turbine, which is under investigation in this research, is 700 *rpm* in steady-state performance, the *rpm* was chosen to be in between of 695 to 705. This range is about one percent (±5 *rpm*) of the nominal speed of the gas turbine (Nikzadfar & Shamekhi, 2011) .

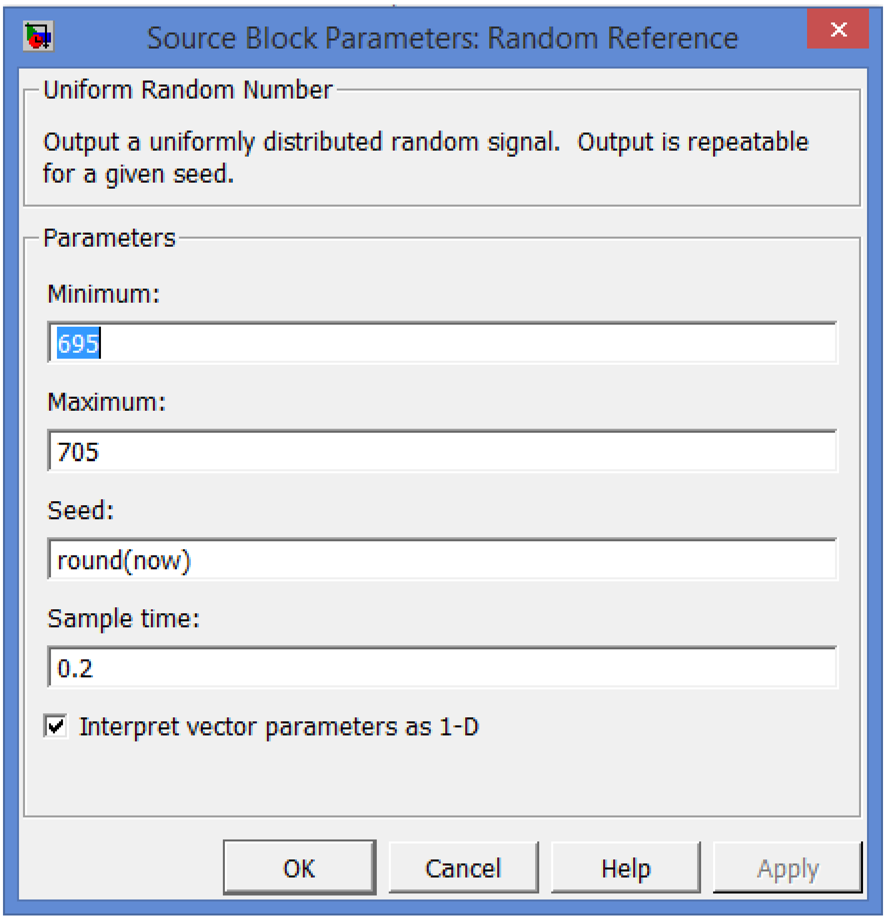
The objective of the controller design is to maintain the rotational speed at a constant value of 700 *rpm* (set point) when the input of the control system changes with the random reference which is a step function. To achieve a satisfactory result, the following criteria are assigned for the response of the system to the random reference ((Balamurugan, Xavier, & Jeyakumar, 2008), (Balamurugan, Xavier, & Jeyakumar, 2008), (Jurado, Ogayar, & Ortega, 2001)):

- *rise time* (T_r) *< 0.5 sec.*

- *settling time* (T_s) *< 2 sec.*

- *maximum overshoot* (M_p) *< 15%*

Figure 4 Random reference block diagram.



Feedback Linearization Control (NARMA-L2)

The nonlinear autoregressive moving average (NARMA) model is a standard model that is employed to represent general discrete-time nonlinear systems. The NARMA model represents input-output behaviour of finite-dimensional nonlinear discrete-time dynamical systems in a neighbourhood of the equilibrium state (Narendra & Mukhopadhyay, 1997). Eqn (5) indicates the mathematical description of the NARMA.

$$y(k+d) = f[y(k), y(k-1), \dots y(k-n+1),\ u(k), u(k-1), \dots u(k-n+1)] \tag{5}$$

where *u(k)* is the system input, and *y(k)* is the system output. A neural network is needed to be trained to approximate the nonlinear function *f* for the system identification stage. Because the NARMA model described by Eqn (5) is slow, an approximate model is used to represent the system. This model which is called NARMA-L2 can be described mathematically according to Eqn (6), where $d \geq 2$.

$y(k+d) = f[y(k), y(k-1), \ldots y(k-n+1),\ u(k), u(k-1), \ldots u(k-n+1)] +\ g[y(k), \ldots y(k-n+1),\ u(k), \ldots u(k-$

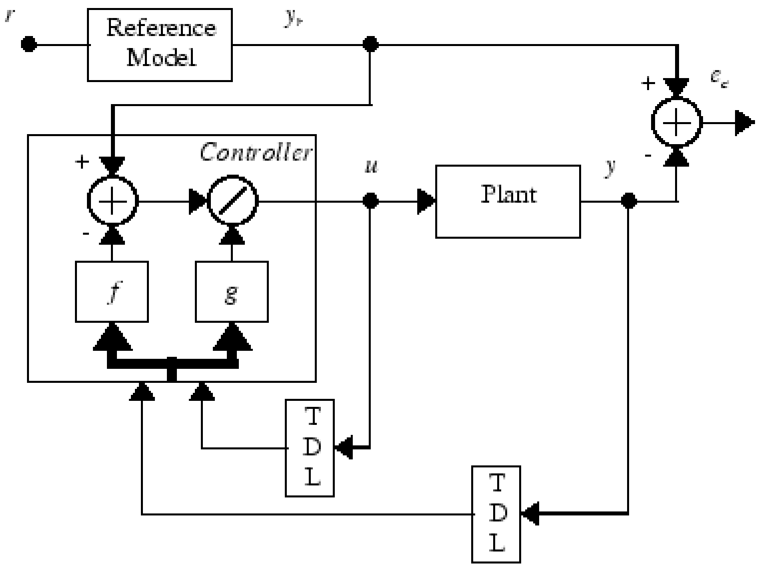
$n{+}1.u(k{+}1)$ (6)

The corresponding controller for NARMA-L2 model is mathematically defined according to Eqn (7), which is realizable for $d \geq 2$.

$$u(k+1) = \frac{y_r(k+d) - f[y(k), \ldots y(k-n+1), u(k), \ldots u(k-n+1)]}{g[y(k), \ldots y(k-n+1), u(k), \ldots u(k-n+1)]} \qquad (7)$$

Figure 5 shows a block diagram of NARMA-L2 controller with approximation functions *f* and *g*, and the time delays *TDL*, all implemented in the NARMA-L2 control block. Controller is a multi-layer neural network that has been successfully applied in the identification and control of dynamic systems (Beale, Hagan, & Demuth, 2011). The main idea behind the NARMA-L2 is transforming nonlinear system dynamics into linear dynamics. It is a rearrangement of the ANN-based plant model which is trained offline.

Figure 5 A block diagram of NARMA-L2 controller (Beale, Hagan, & Demuth, 2011).



Design of NARMA-L2 Controller

NARMA-L2 controller block has been already implemented in Simulink-MATLAB. There are two main steps in using NARMA-L2 including system identification and control design. In system identification stage, a neural network model of the plant is developed. This stage includes the block diagram representation of the system identification and the training process. The closed-loop diagram of the control system for the gas turbine engine system with the NARMA-L2 controller is similar to Figure 3, when the controller block is replaced by NARMA-L2 controller block which is shown in Figure 6.

Figure 6 NARMA-L2 control block (Beale, Hagan, & Demuth, 2011).

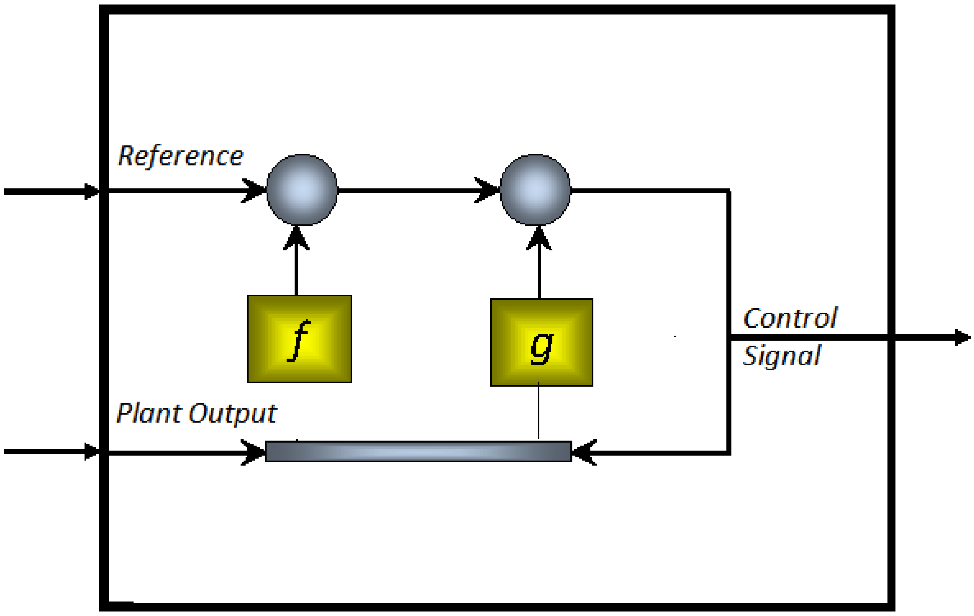
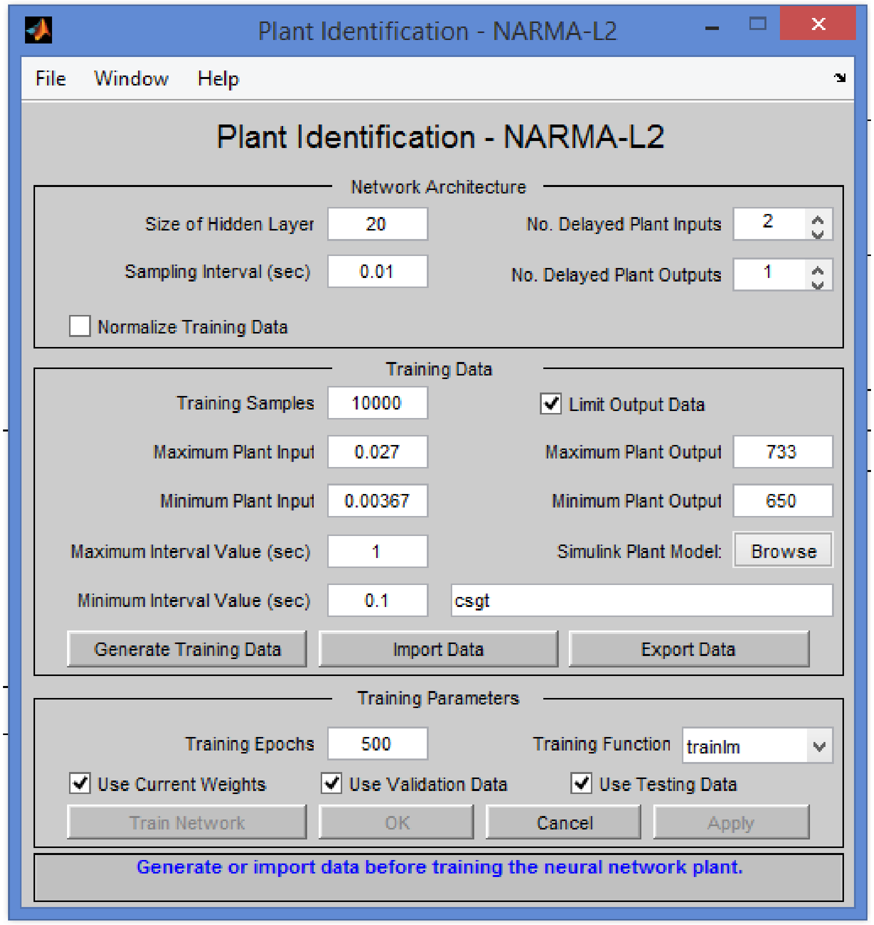


Figure 7 shows the block diagram of the plant identification for the control system of gas turbine (CSGT) which uses the NARMA-L2 controller with all the adjusted parameters for the generating data, and training the neural network model of the system.

Figure 7 Gas turbine system identification block diagram for NARMA-L2.



As it is seen from Figure 7, minimum and maximum values for the plant input (fuel mass flow rate) are 0.00367 and 0.027 *kg/s*. For the plant output (rotational speed), minimum and maximum values are 650 and 733 *rpm* respectively. Before the neural network training stage was performed, 10000 data sets for the GT input and output was generated by considering the minimum and maximum interval values as 0.1 and 1 seconds. These data were generated using the option *Generate Training Data*. The integrated program can generate training data by applying a series of random step inputs to the Simulink model of the plant. The size of the hidden layer and the number of delayed plant inputs and outputs were adjusted at 20, 2, and 1 respectively. The sampling interval was fixed on 0.01 second. The training proceeded according to the selected training function (*trainlm*). After the training was completed, the response of the resulting plant model was displayed, as in Figure 8. Separate plots for validation data is shown in Figure 9. As it is seen from Figures 8 and 9, the results of training for neural network model of the GT are satisfactory.

Figure 8 Training data for NARMA-L2 controller.

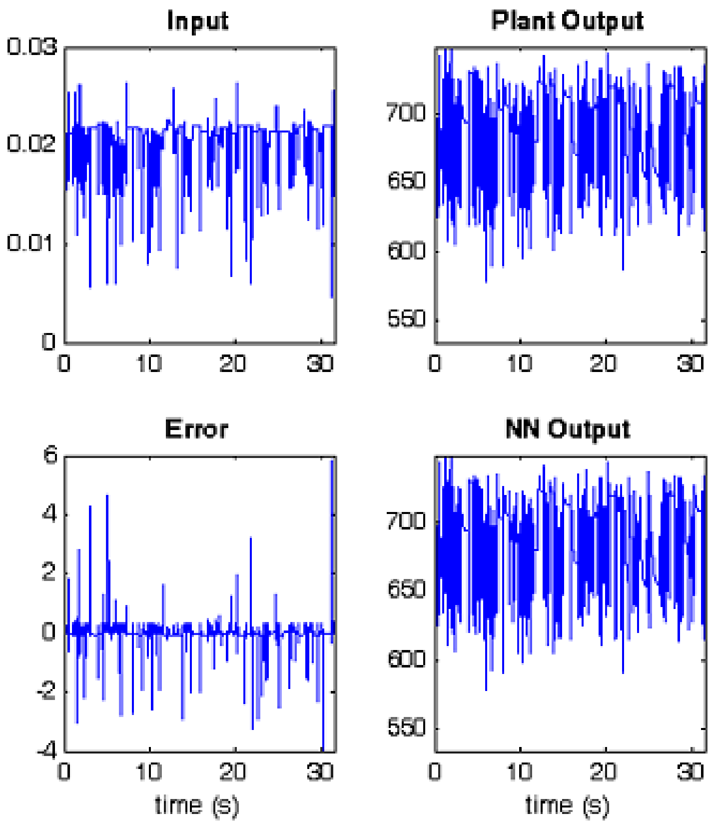
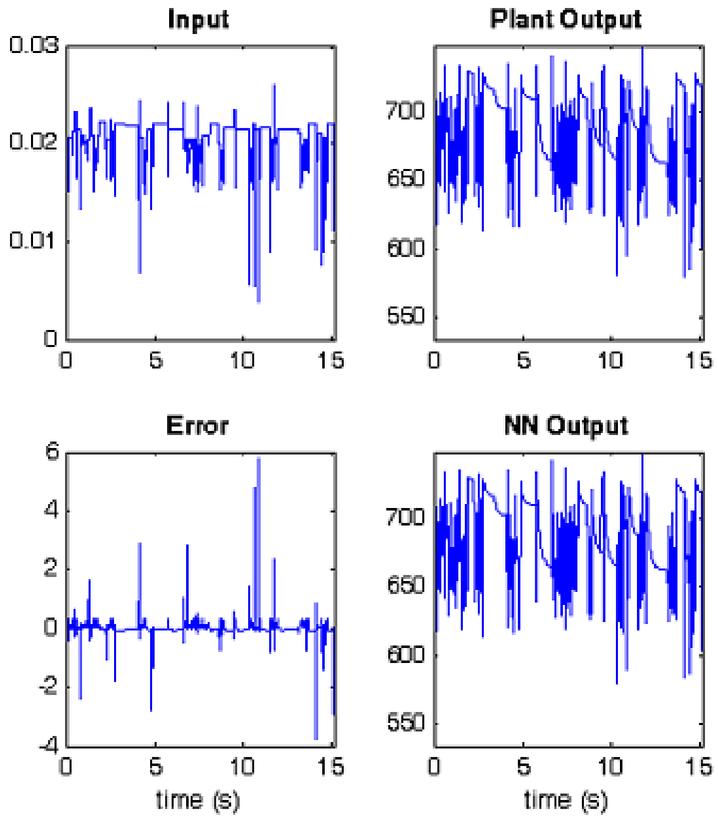


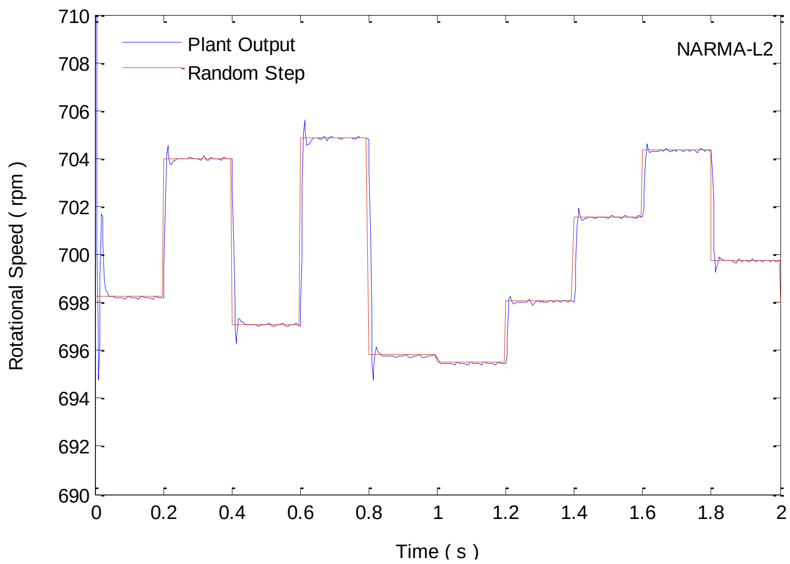
Figure 9 Validation data for NARMA-L2 controller.



Simulation of NARMA-L2 Controller

Simulation is the last stage of NARMA controller design. At this stage, the closed-loop control system can be run to simulate the whole system. The result of simulation is shown in Figure 10. The result shows that NARMA-L2 controller can accurately follows the value and trend of changes in the system input. Besides, the reaction of the controller to the input changes is very fast and satisfies the design criteria in terms of rise time, settling time and maximum overshoot.

Figure 10 Response of gas turbine system with NARMA-L2 controller to random step inputs.



PID Control

A proportional-integrator-derivative (PID) controller was firstly introduced to industry in 1939 and has remained the most widely used controller in industrial control systems until today (Araki, 1984). PID is a generic feedback control system that acts on the basis of difference between values of a measured process variable and a desired set point. The controller objective is to minimize this difference, which is called error, by adjusting the process control parameters. The PID controller includes the proportional (*P*), the integrator (*I*) and the derivative (*D*) values that can be interpreted in terms of time. *P*, *I*, and *D* respectively depend on the present error, accumulation of past errors, and prediction of future errors (Araki, 1984). By tuning these three parameters, the controller can provide the required control action designed for a specific process. Based on the application, it is also usual to use just *PI, PD, P* or I controllers. The popularity of PID controllers is specifically because of their flexibility for giving the designer a larger number of design options on the basis of the system dynamics. The PID algorithm is described by Eqn (8).

$$u(t) = K\left(e(t) + \frac{1}{T_i}\int_0^t e(\tau)\,d(\tau) + T_d\,\frac{de(t)}{d(t)}\right) \tag{8}$$

where *y* is the measured process variable, *r* is the reference variable, *u* is the control signal and *e* is the control error. The controller parameters are proportional gain K, integrator time T_i, and derivative time T_d. The control signal is thus a sum of three terms including P, I and D. The reference variable is often called set point (Åström, 2002).

Design of PID Controller

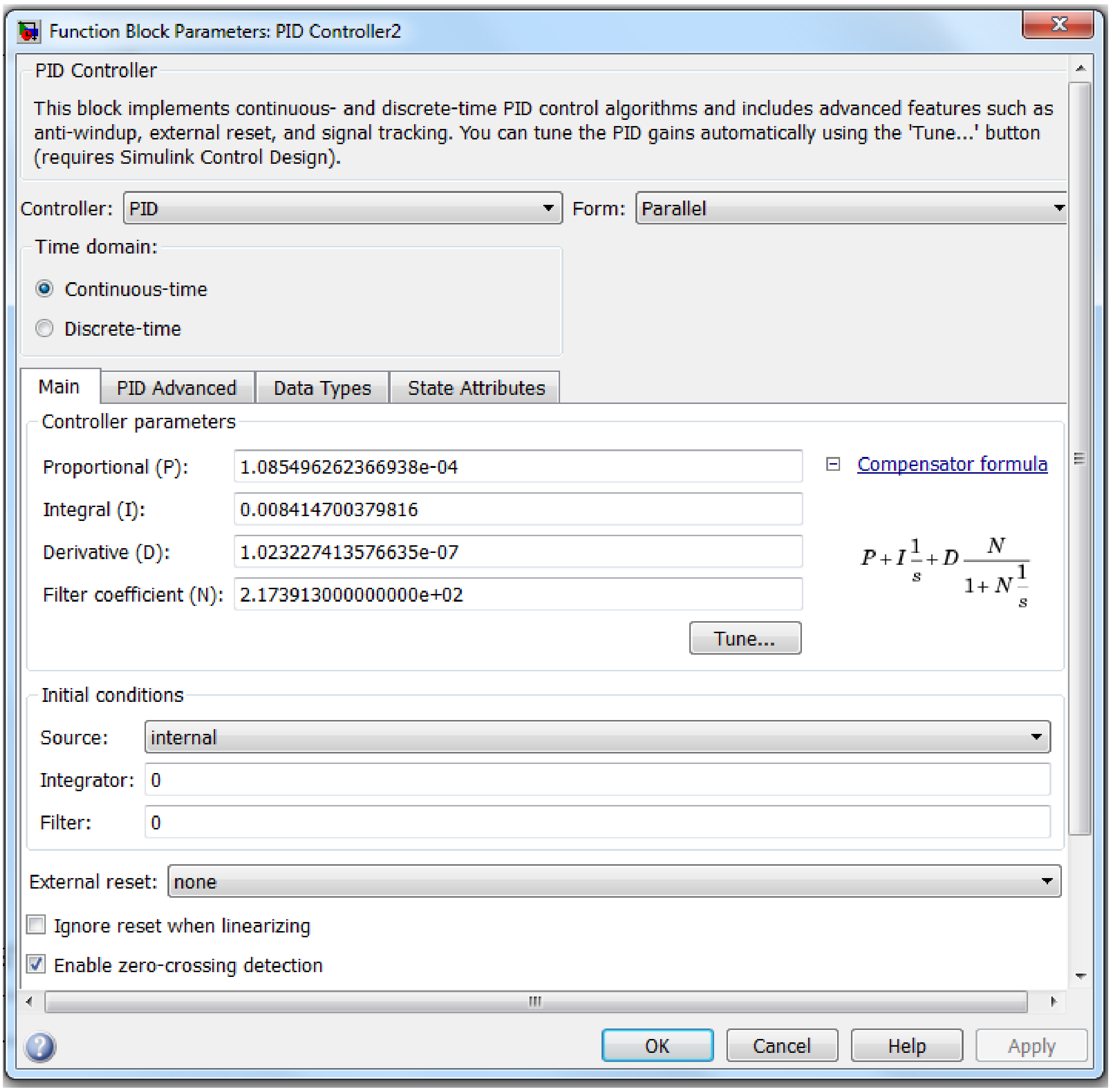
PID controller block has been implemented in the Simulink-MATLAB and its gains are tuneable either manually or automatically according to the PID tuning algorithm in MATLAB. The closed-loop diagram of the control system for the gas turbine engine system with the PID controller is also similar to Figure 3, when the controller block is replaced by PID controller block implemented in MATLAB.

The objective of tuning the PID gains is to achieve a good balance between performance and robustness, while keeping the closed-loop stability. Therefore, the tuning is performed in a way that the closed-loop system tracks reference changes, suppresses disturbances as rapidly as possible, and its output remains bounded for bounded input. Besides, the loop design should have enough gain margin and phase margin to allow for modelling errors or variations in system dynamics. According to the algorithm, at the first stage of the tuning, an initial controller is designed by choosing a bandwidth to achieve the balance between performance and robustness based upon the open-loop frequency response of the linearized model. When the response time, bandwidth, or phase margin is interactively changed using the PID tuner interface, the new PID gains are computed by the algorithm. This process continues until the desirable PID controller is achieved (Beale, Hagan, & Demuth, 2011). According to the algorithm, Eqn (9) can be written as follows:

$$u = P + I\,\frac{1}{s} + D\,\frac{N}{1+N\frac{1}{s}} \qquad (9)$$

where P, I and D are proportional, integrator and derivative gains respectively. N is filter coefficient. Figure 11 shows the PID control algorithm block with the values of tuned PID gains for the gas turbine engine system.

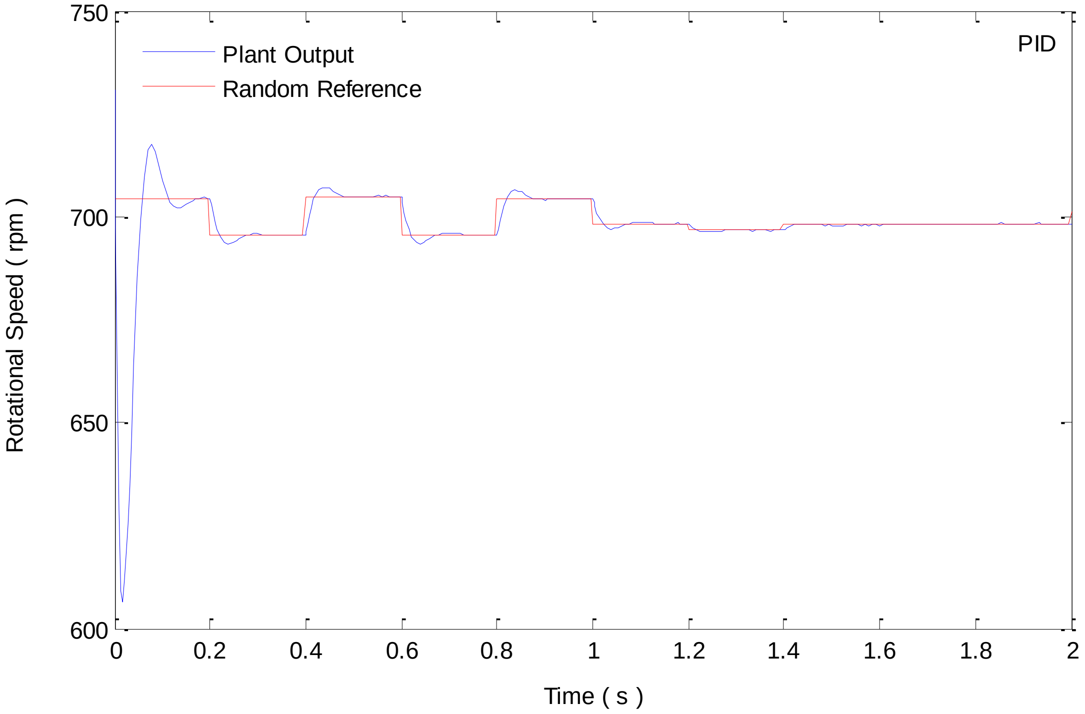
Figure 11 PID control algorithm block for tuning PID gains.



Simulation of PID Controller

After the completion of PID controller design, the closed-loop control system can be run to simulate the whole system. The result of simulation is shown in Figure 12. As it is seen from this figure, the response of the controller to the changes of the system input is fast, and after about 0.2 second, it is stabilized and followed the value and trend of the changes. The reaction of the controller to the input changes satisfies the design criteria in terms of rise time, settling time and maximum overshoot.

Figure 12 Response of gas turbine system with PID controller to random step inputs.



Comparison of Controllers Performances Based on the Design Criteria

To compare the results of performances for the designed controllers, they were run in a common Simulink environment with the same input for their control systems. Figure 13 shows the resulting Simulink model including the designed NARMA-L2, and PID controllers. Specifications of the random reference (step function) and the gas turbine system for the controllers are the same as already discussed in this paper. The simulation was run for two seconds which was enough time for capturing the complete dynamics of the controllers. Figure 14 shows the performances of the controllers. Figures 15 and 16 show the same performances from closer perspectives to the set point of rotational speed (700 rpm) and the initial response respectively. As it is seen from Figures 14, 15 and 16, the two controllers satisfy the controller design objectives in terms of rise time, settling time and maximum overshoot. It can be seen that the NARMA-L2 controller has a superior performance to the PID. It follows the value and trend of the changes faster and more accurately than the PID. The values of settling time, rise time and maximum overshoot of the response of the NARMA-L2 are less than the corresponding values of the conventional PID controller.

As it is seen from Figure 16, the step response of the gas turbine system, with each of the controllers, starts with an *undershoot*. This is because the gas turbine is a non minimum phase (NMP) system. From the controller point of view, a non minimum phase system is the one that its transfer function has one or more poles or zeros in the right half of the complex plane. A NMP system behaves faulty at the start of the response with an *undershoot*. The output becomes first negative before changing direction and converging to its positive steady-state value. This kind of behaviour, which makes the response slow, could arise due to time delay in the system. NMP phenomenon has been already observed in gas turbine systems (Holsonback, 2007). However, as it is seen from Figure 16, the controllers could quickly correct this behaviour and bring the system to a stable situation. The reaction of the NARMA-L2 to the faulty behaviour is much quicker than the PID controller. The previous experience and research results have demonstrated that if the response is well-controlled by designing a suitable controller, then NMP phenomenon does not make a problem for operation of gas turbines (Holsonback, 2007).

Figure 13 Simulink model of the ANN-based (NARMA-L2) and PID controllers for a single-shaft gas turbine.

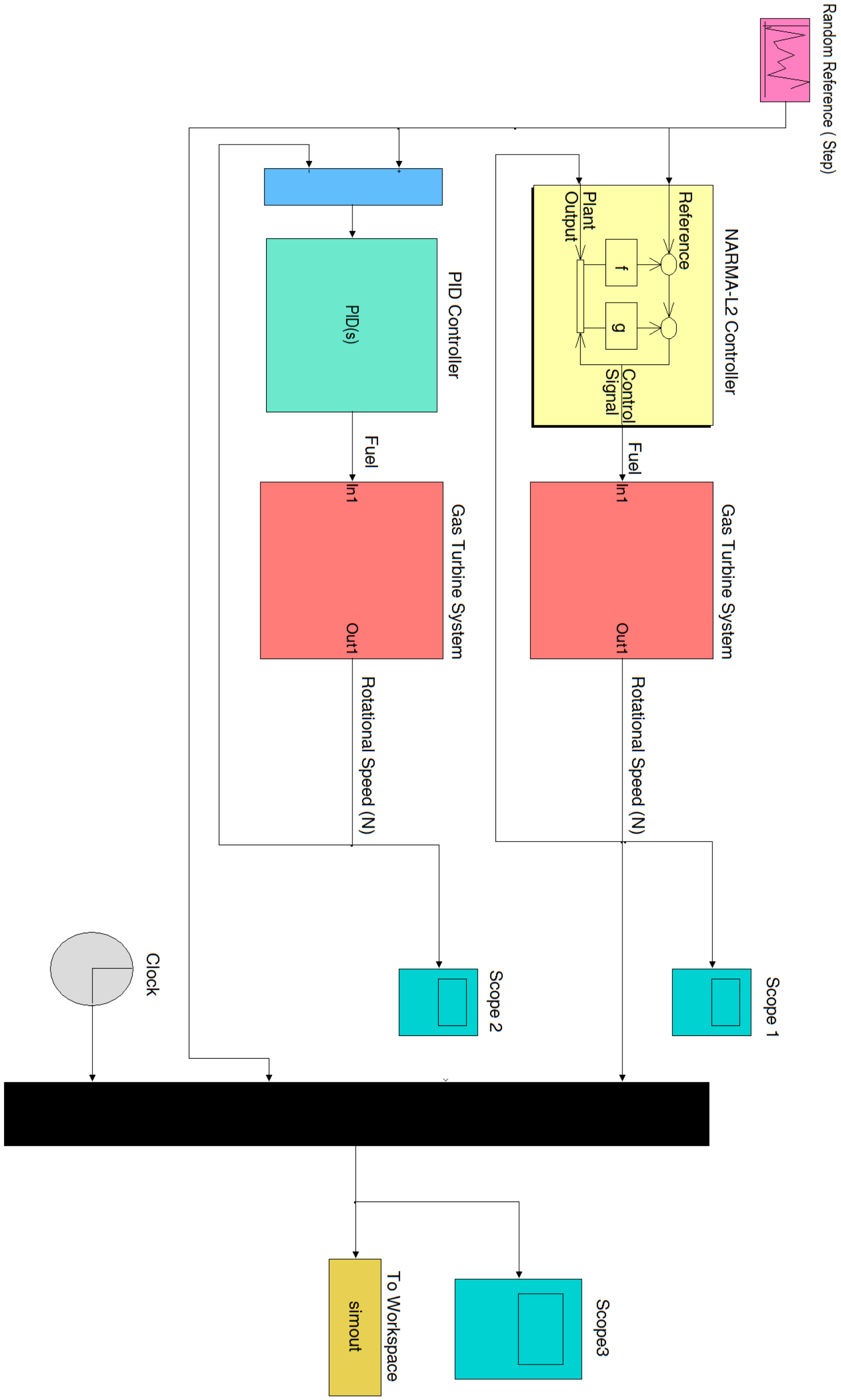


Figure 14 Performances of two different controllers for a single-shaft gas turbine.

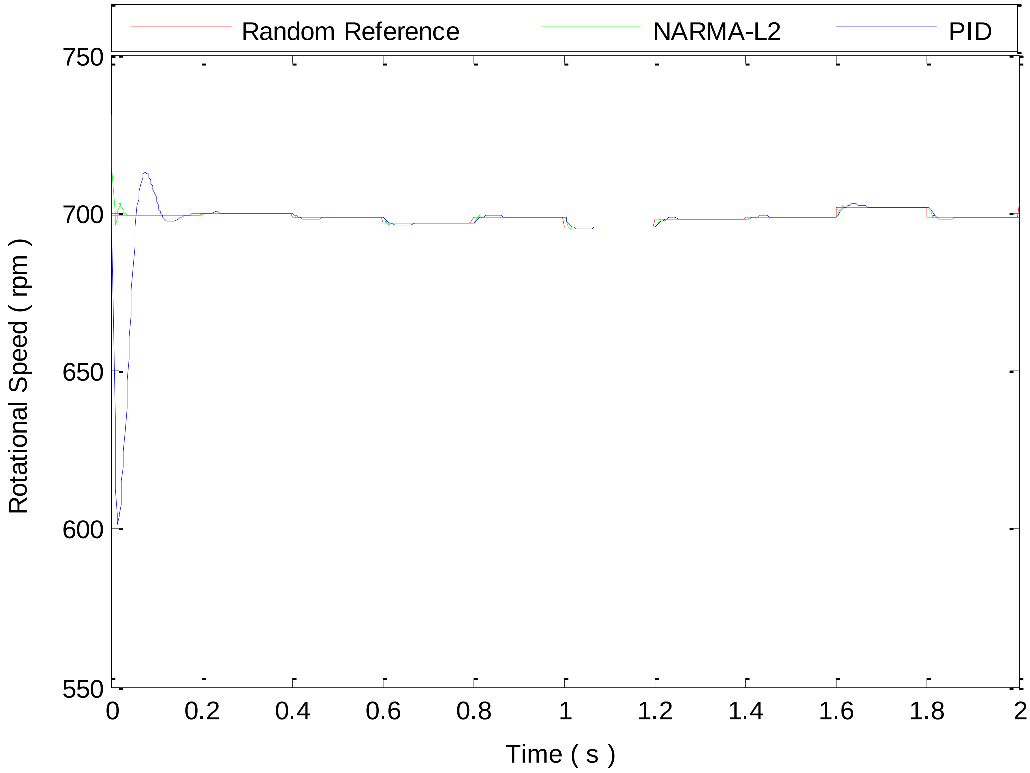


Figure 15 A close-up perspective of the performances of two different controllers for the gas turbine.

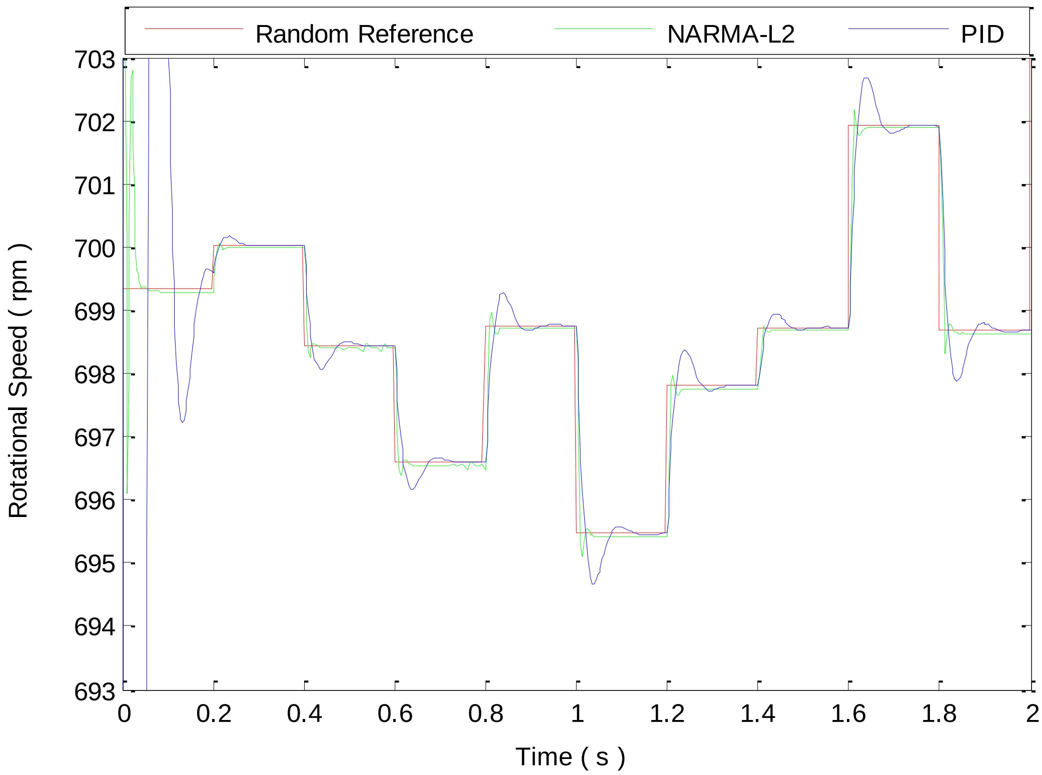
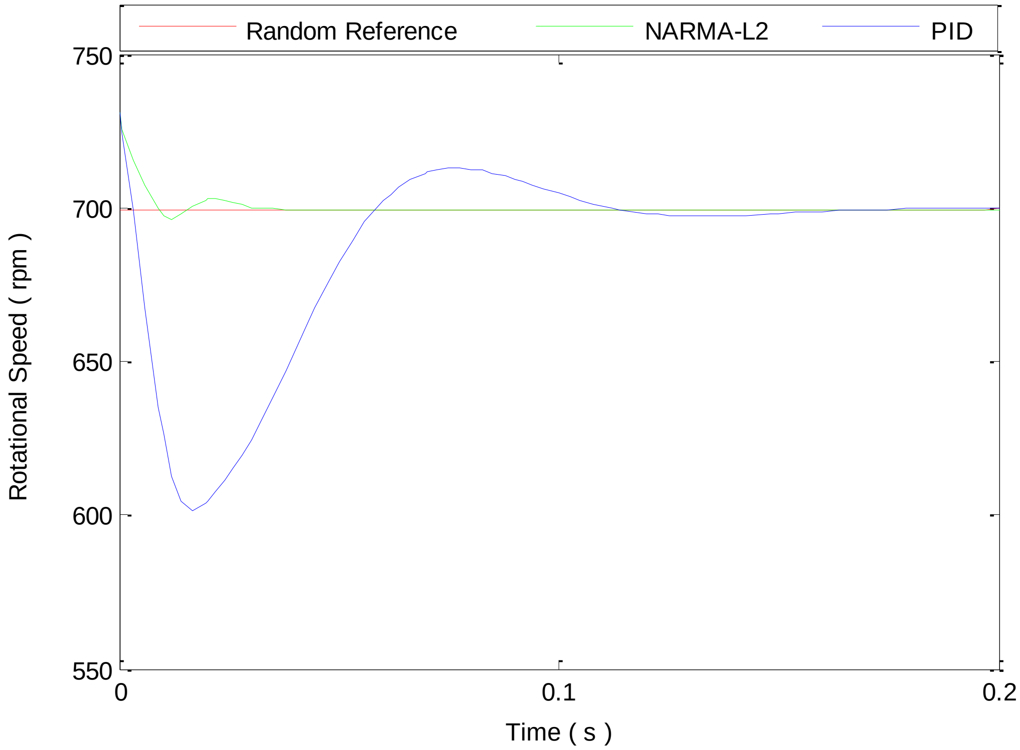


Figure 16 A close-up perspective of the initial respons of two different controllers for the gas turbine.



Comparison of Controllers Performances Based on the Performance Indices

In addition to rise time, settling time and maximum overshoot, the performance of PID and NARMA-L2 controllers can be compared on the base of performance indices which are quantitative measures of the performance of a system. These measurements and calculations are used to evaluate and optimize the performance of a control system and to design an optimum system (Dorf & Bishop, 2010). In this study, the performance indices, defined according to Eqn (10), (11), (12), and (13), were used for comparison of the controllers' performances.

- The integral of the square of the error (*ISE*)

$$ISE = \int_0^T e^2(t)dt \tag{10}$$

- The integral of the absolute value of the error (*IAE*)

$$IAE = \int_0^T |\mathrm{e}(t)|dt \tag{11}$$

- The integral of the time multiplied square of the error (*ITSE*)

$$ITSE = \int_0^T te^2(t)dt \tag{12}$$

- The integral of the time multiplied absolute value of the error (*ITAE*)

$$ITAE = \int_0^T t|\mathrm{e}(t)|dt \tag{13}$$

where *e* is the steady-state error of the controller. Each of the above indices is calculated over some interval of time $0 \leq t \leq T$. *T* is chosen to span much of the transient response of the system. *T* is usually chosen as the settling time T_s. The best selectivity of the performance indices is when the minimum value of the integral is readily discernible as the system parameters are varied. *ISE* discriminates between excessively over-damped systems and excessively under-damped systems. The minimum value of *ISE* occurs for a compromise value of the damping. *IAE* is specifically employed when computer simulation is required. *ITAE* is useful when the goal is to reduce the contribution of the large initial error to the value of the performance integral, and/or to place an emphasis on errors occurring later in the response. It provides the best selectivity of the performance indices. *ISE* and *IAE* weight the error equally over the entire interval, while *ITSE* and *ITAE* give higher weight to the error at later times, so that the system is not penalized for having large initial error (Dorf & Bishop, 2010).

Figures 17 to 20 show the results of comparison of the controllers' performances on the base of *ISE*, *IAE*, *ITSE*, and *ITAE* respectively. As it is seen from these figures, the NARMA-l2 controller shows a superior performance to the PID one. This result is in agreement with the result obtained from the comparison already made in prior section, on the base of design criteria of the controllers.

Figure 17 ISE for NARMA-L2 and PID controllers.

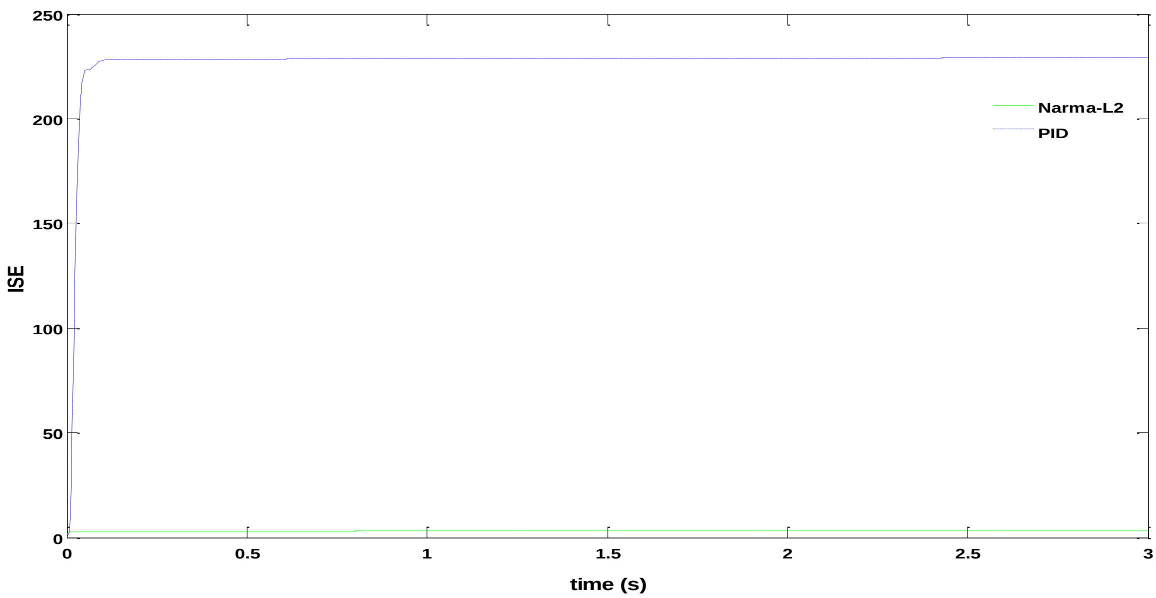


Figure 18 IAE for NARMA-L2 and PID controllers.

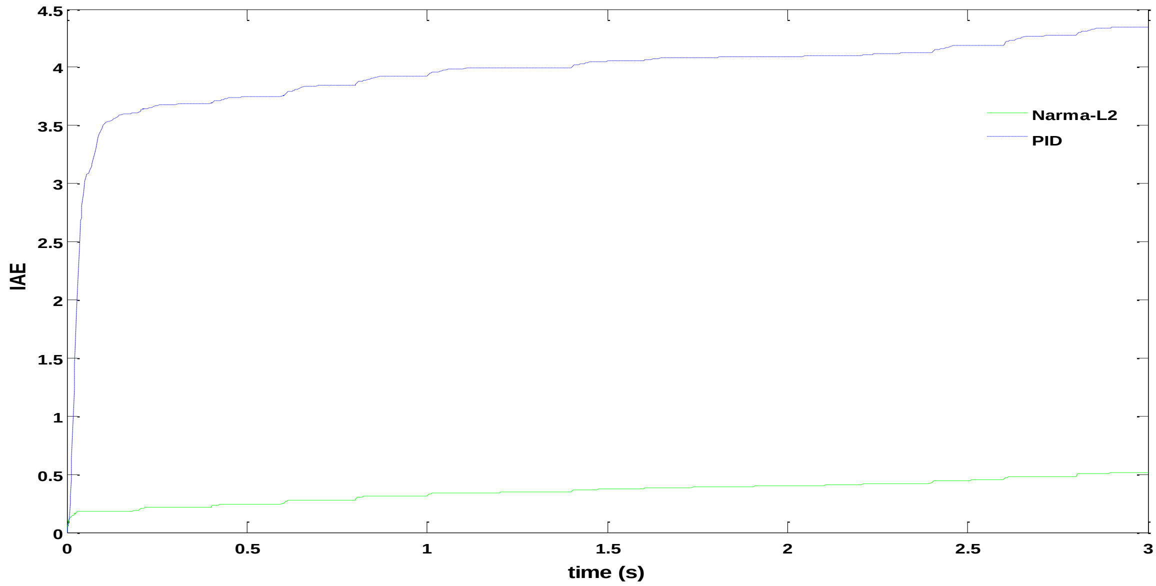


Figure 19 ITSE for NARMA-L2 and PID controllers.

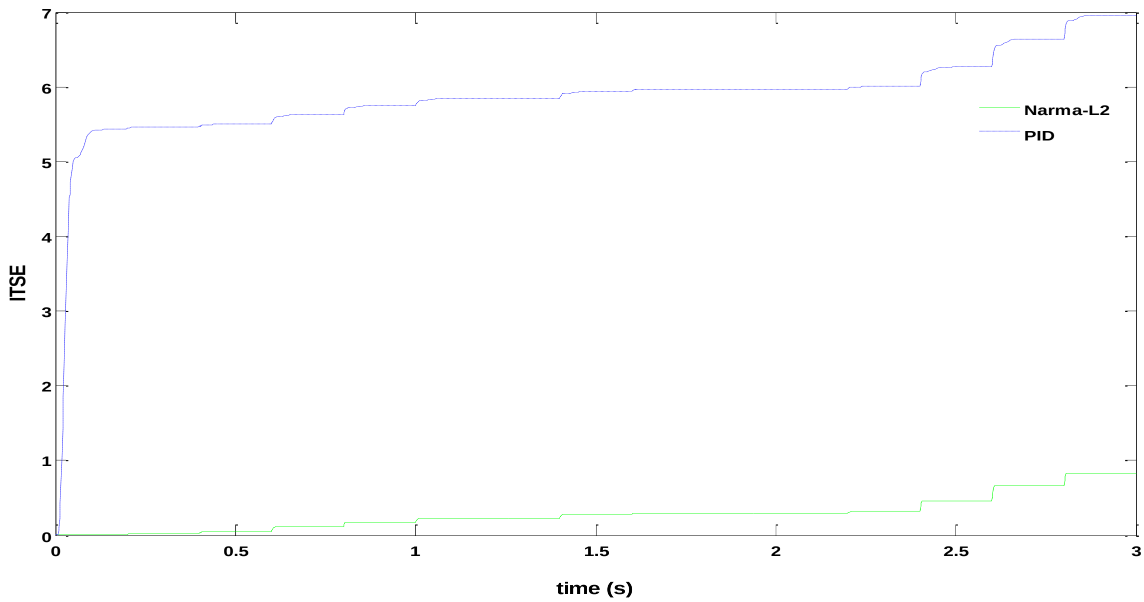
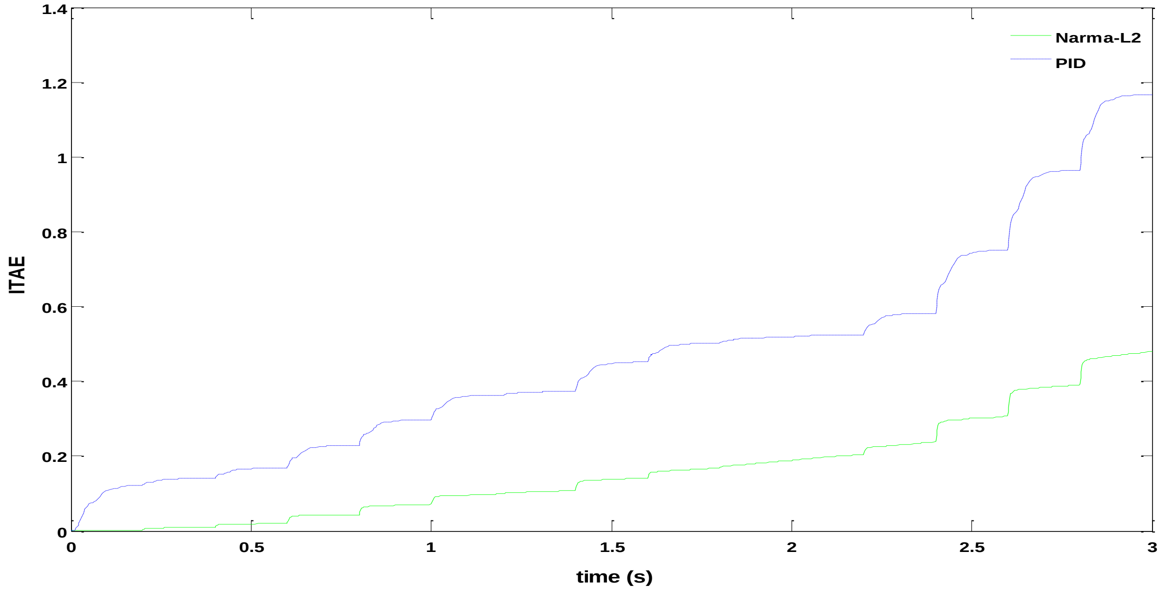


Figure 20 ITAE for NARMA-L2 and PID controllers.



Conclusions

This study investigated design and application of a PID and a neural network based controllers (NARMA-L2) for an aero gas turbine engine. Fuel mass flow rate and rotational speed were considered as input and output of the plant (gas turbine system) for control purpose respectively. The objective of the controllers design was to maintain the rotational speed at a constant value when the input of the control system changes with the random reference. After the system identification processes were completed and the neural network plant models were developed, the relevant parameters for all controllers were tuned and set up according to the requirements of the controller design for the gas turbine. To compare the performance results for the two controllers, they were run in a common Simulink environment with the same input for their control systems. Results show that the NARMA-L2 has a superior performance to the PID, in terms of the design criteria, and that it follows the value and trend of the input changes faster and more accurately. Besides, the performance of PID and NARMA-L2 controllers were compared on the base of performance indices *ISE*, *IAE*, *ITSE*, and *ITAE*. The results from this comparison were in agreement with the results obtained from the comparison made on the base of the design criteria. Overall, it is concluded that artificial neural networks have a strong potential to be considered as a reliable alternative to conventional modelling and control methodologies.

The application of each of white-box and black-box controllers to gas turbines could be used for both white-box and black-box models. It means that four different combinations could be employed. In this paper, two of these approaches were explored. The other two combinations could be the subjects of further research in this field in the future. By improving the capabilities of ANN-based controllers in control of gas turbines and also by improvement of the plant modelling, it would be possible to make the system to be more tolerant against the faults and disturbances.

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Nomenclature

AMPC=approximate model predictive control

ARX =autoregressive with exogenous input

CCGT=combined cycle gas turbine

CSGT=control system of gas turbine

D=derivative

GPC=generalized predictive control

GT=gas turbine

I=integrator

IAE=integral of the absolute value of the error

IGV=inlet guide vanes

IPGT=industrial power plant gas turbine

ISE=integral of the square of the error

ITAE=integral of the time multiplied absolute value of the error

ITSE=integral of the time multiplied square of the error

MGT=micro gas turbine

MPC=model predictive controller

NARMA=nonlinear autoregressive moving average

NARMA-L2= nonlinear autoregressive moving average with feedback linearization

NARX=nonlinear autoregressive exogenous

Neurocontrol=neural network based controller

NMP=non minimum phase

NMPC=nonlinear model predictive control

P=proportional

PD= proportional—derivative

PI=proportional-integrator

PID= proportional-integrator-derivative

RBFNN=radial basis function neural network

rpm=revolution per minute

TDL=time delay

UPFC=unified power flow controller

VSV=variable stator vane