International Journal of Electronics and Communication Engineering.
ISSN 0974-2166 Volume 5, Number 5 (2012), pp. 567-590

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Discrete Time Quadratic Neuro-Genetic Approach for Satellite Attitude Control

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Abstract

Nowadays, attitude control systems demand better performance, resulting in the application of the new advanced nonlinear control theory. In this paper, a new technique is proposed to design an optimal Discrete Time Quadratic Neuro-Gentic (DTQNG)approach for the fast state feedback control of satellite. The proposed DTQNG approach has an excellent ability to provide more robust and faster response than common linear state feedback controllers. Spin stability criteria of satellite about stable and unstable axis are shown. Robustness of satellite is considered in theproposed approach. Long life time, and fast response for the satellite, the deviation of the satellite from its nominal position, and the time of deviation are included in the optimization objective function.

Keywords: Discrete-Time Dynamic Neural Unit-Genetic Algorithm-Satellite Attitude Control-Spin Stability of the satellite.

Introduction

The satellite carries on board different equipment forremote sensing and telemetry which needs to be preciselypointed to the earth. The satellite may receive animpulsive torque from any particles moving in the spacewhich results in deviation of the satellite from its attitude.This deviation will result in a poor imaging andcommunications with the ground stations. An attitudecontrol must use to return the satellite back to itsorientation [1].An extensive research was done to control the attitude ofthe satellites using classical control techniques [2].However these types of controllers have a limitedcapability and they are usually linear and require anaccurate model. The fuzzy logic control (FLC) is wellknown of its robustness, suitability for handling linearand non-linear model, ability to handle impreciseknowledge and ill-defined system [3].A nonlinear *observer* is proposed, for reconstructing the state variables of a spacecraft. Then existing feedback control laws areused, giving a system which is asymptotically stable in a specific region [4].An observer based method, for a reaction wheel attitude controller, is proposed in [5], while various control laws for a three reaction wheel, three magnetic torque configurations are found in [6].Methods of geometric mechanics for stability analysis of rigid body dynamics was discussed in [8].

Another feedback controller incorporating gain-scheduled adaptation of the attitude gains is developed for a linearized model of a gravity gradient stabilized spacecraft in [9]. The simulations are done for the *SpaceStation Freedom*. In [10]evaluate the performance and stability of both classical and modern controllers for the *Space Station Freedom*. A simulator description of the *Space Station Freedom* with the McDonnellDouglas Space Systems Co./Honeywell Attitude Control System can be found in [11].More general methods for the design of spacecraft simulators can be found in [12]. A plume flow model to calculate the forces and the heat transfer caused by the firing of attitude control thrusters on satellites is developed in [12].

Various attitude control laws, for a space station, in the case of absence of disturbances using Lyapunov’s second methodwas discussed in [13]. Satellite attitude control laws using Lyapunov’s methods are also the subjects of [14], [15], [16] and [17].

The application of a game theoretic control approach, combined with internal feedback loop decomposition for uncertainties in the moments of inertia of a space station (which are considered constant in time) is described in [17].[18] considers a control law, for a class of uncertain nonlinear systems which can be decoupled by state variable feedback. The law is based on the technique of variable structure and is applied for the control of an orbiting spacecraft which uses reaction jets.

In [19] a method based on the algebraic theory of rational fractions, for the control of a spinning satellite using gyro-torquers, is discussed. Attitude control using gyro-torques is also considered in [20]. The attitude control (pitch and roll) of automobiles is the topic in [21].

Optimal control using nonlinear programming techniques with application to satellite attitude control is discussed in [22]. [23]propose a device for the direct measurement of the attitude stability of a space station, while [24] present a technique for attitude determination. Three axis attitude control of a rigid body spacecraft using a sliding-mode control law is described in [25]. The approach is valid as long as sliding motion is maintained and the extreme values of the plant dynamic parameters are known.

In [26] a Kalman filter is used to estimate local magnetic field and perform magnetic attitude control for the *GP-B* satellite, which was scheduled to be flown in 1996. [27]introduced the use of a gravity-stabilized tether attached to a non spinning part of a satellite, for enabling its attitude control by employing conventional control systems.

An enhancement in the solving techniques for the two-point boundary value optimal attitude control problem is presented in [28]. Various problems, advantages and disadvantages in different choices, associated with the design of a space station control system are discussed in [29].

[30] and [31] presented an approach to the three-axis attitude control of a spacecraft-beam-tip body system, based on inevitability results. Momentum management systems designed to face the problem of momentum saturation of the control moment gyros, due to noncyclical external torques acting on the space station, are considered in [32] and [16].

A near optimal orbit and attitude control system, for a plate-like rigid spacecraft in geostationary orbit, is presented in [33] . All the results and conclusions are based on simple linear models. A fuzzy logic controller for the control of a spacecraft is applied in [34].

[35]Proposes a control law for single axis rotational maneuvers of a spacecraft-beam-tip body (an antenna or reflector), in the presence of an unknown but bounded disturbance torque, acting on the spacecraft. In [36], impulse response functions are used for the selection of control switch times, in the bang-bang control of linear, elastic slewing satellites. A bang-bang control law is also presented in [37].

The nullification of the accumulated effect of the modeling errors, achieved by a correction in the control to induce the physical system to have a behavior close to the reference model, is the subject in [38]. A parameter optimization procedure is applied to find the gains of the described method.

[39]employed a PI compensator augmented by a Kalman filter, to control the communications beams and the attitude angles of a flexible spacecraft. They explored two design methods: the first one based on Eigen-value analysis and the second based on singular value criteria. A review in attitude control systems and beam pointing accuracy can be found in [40], while a general framework for the analysis of attitude tracking control problems can be found in [41] and [17].

[42]proposes a control law for asymptotic function reproducibility of a class of nonlinear systems, such that the output of the system tends asymptotically to a given function. Based on this control law, a nonlinear feedback control law is then derived for the attitude control of a satellite containing symmetric rotors.

The application of a controller consisted of a servo-compensator, a stabilizing feedback loop and a feed forward compensator, to the design of a vertical takeoff and landing aircraft flight control system is discussed in [43].

[44]studied aircraft attitude control systems, based on the optimal control model of the human pilot. The optimal control human pilot model has its genesis in the hypothesis that, with limitations and in specific well-defined control tasks, the human pilot can be described in terms of the operation of a linear optimal estimator and regulator. Geometric control theory for rigid body attitude control is considered in [45].

A simple two-surface solar controller is described and applied for the attitude control of a spacecraft in [46] and [47]. A proportional plus derivative control law for attitude control of non rigid body spacecraft is found in [48]. [49]a decomposed controller which consists of two coupled electronic integrators is introduced, for satellite control.

The dynamics of *UOSAT* (low orbit satellite with a principal axis pointing towards the Earth center and a minimum number of sensors and hardware) and its control using the on-board magnet torque is given in [50].

[51] Describes the dynamic modeling and control of the *SPOT* French Earth observation satellites. In [52] it is shown that the knowledge of the Voyager's limit cycle motion, as measured by the celestial and the inertial sensors, is adequate to estimate a selected number of errors, which adversely affect the spacecraft attitude knowledge.

An extensive research was done to control the attitude of the satellites using classical control techniques. However these types of controllers have a limited capability and they are usually linear and require an accurate model which assumed as *first knowledge gap*.

Neural networks, or neuro-controllers, constitute much of the recent non linear time invariant (LTI) control research. Because neural networks are both nonlinear and adaptive, they often realize far superior control compared to LTI.

However, dynamic analysis of Neuro-controllers is mostly intractable thereby prohibiting control engineers from ascertaining their stability status. As a result, the use of Neuro-controllers is primarily restricted to academic experiments; most industrial applications require guarantees of stable control which have not been possible with neural networks, we can assume it as *second gap in knowledge*.

Even for using artificial neural networks as locally predictive network for the attitude control problem, every time the system dynamics change in an unknown way, *it will be assumed* that a Neuro-model describing the new dynamics of the satellite has been trained according to this methodology. In practice, since vanilla back propagation converges rather slowly and sometimes unreliably, this would require some other method for rapidly learning a dynamic model which acts *the third knowledge gap*. Also fuzzy logic controller depends on the initial attitude of the satellite.

The fourth gap of knowledge is this limits the possibility of a real time implementation since generally the initial attitude is not known in advance [53].

However, at current there is a paucity of research dealing with the question of how to construct an adaptive approach to learn how to identify and control satellite attitude.This and other related questions are sought to be answered in this study concerning the identification and control of process modeling satellite attitude control problem.

Discrete Time Quadratic Neuro-Genetic Approach to Solve Satellite Attitude Control Problem

As real-time systems become larger and more complex, challenges of creating the control system have raised. Musliner identifies some of the problems that a developer of a real-time system must take into consideration [54]. The application must be able to sense the surrounding environment and be able to adapt to the output from it. In normal real-time systems an example of this is that an embedded flight control system can change mode from normal flight to landing when the plane comes close enough to the landing field. It is no use to have all the parts of the system activated all the time. Artificial intelligence comes in handy when the boundaries between different phases are not that clear any more. The system in this situation will adapt easier to the environment. Musliner et al. also divide the solutions into three different categories [54]:

i. Embedding artificial intelligence into a real-time system - The artificial intelligence subsystem must meet the deadline but does not have to care about the rest of the problems associated with real-time systems.
ii. Embedding real-time reactions into an artificial intelligence system – This is the opposite idea where the artificial intelligence system must implement all the real-time functionalities.
iii. Coupling artificial intelligence and real-time subsystems as parallel, cooperating components - This type tries to take the best from both subsystems and combine them.

Hamidzadeh and Shekhar propose a methodology that can be used during design to get a formal specification of the real-time problem when artificial intelligence is used in the solution. They split the time of the artificial intelligence algorithm into two phases. The first is the planning phase where the artificial intelligence algorithm searches for a solution that will be used during training. The second phase; the execution phase. They discuss and compared alternative algorithms to come up with which of them that is most suited for different problems [55].

The genetic algorithm can at any time be interrupted and it will have an answer. This differs from many other algorithms that must finish before they can present an answer at all. The normal genetic algorithm can in theory have a very bad worst case response. When the answer is used in a hard real-time system, a genetic algorithm will not be the best solution for this type of system because of the insecure answer. Genetic algorithms fit a soft real-time system. Dasgupta has studied real-time systems where the optimum changes over time. This is often the case in real-time systems because of changes in the environment around the systems. The solution that Dasgupta proposes is to use a structured genetic algorithm. The algorithm keeps more of the genetic material which makes it less sensitive to changes of the optimum. Dasgupta compares the structured genetic algorithm to a standard genetic algorithm with a high mutation rate. The high mutation rate compensates for the problem that a standard genetic algorithm has to find the shifting optimum [56].

This study proposed the controller using the Genetic Algorithm (GA) with this predictive capability we can now evaluate a large number of hypothetical control inputs and select the best.GA is used to explore the space of hypothetical control inputs at any given moment and the DNU predictor to evaluate any member of the current population (of hypothetical control inputs). Normally the evaluation phase (computing the fitness of a member of the population) is the most time consuming aspect of the genetic algorithm, but the study proposes to use DNU for this phase, thus allowing the evaluation of many thousands of sets of control inputs over the relevant prediction interval which may be a significant fraction of a second. Of itself the GA is very simple. The control signals are represented by binary strings, with simple bit string manipulations for crossover and mutation. A variety of implementations could be used for the GA ranging from execution by a serial processor, to gate arrays with additional memory and processors (to provide a stack, for example). Given that the evaluation time per member of the population is very fast, the rest of the GA is quite simple. The particular implementation chosen would depend heavily on the system to be controlled and the speed of events in the real world.

The researcher calls this mixture of techniques a Neuro-Genetic control approach. The learning phase of the neural network can be likened to basic mastery of motor control to the extent that one can predict the immediate consequences of any given set of actions. The genetic component of the system is analogous to a series of 'mind experiments', as shown in Figure (1) using many of these predictions to choose an actual set of control signals.

The sequence of events is thus Figure (1), $t = k\ \Delta t$, with$\Delta\ t = 0.01$(in the simulations)

At step k-1. Controller applies $u^*(k-1)$, DNU predicts $x^q(k)$

At times between k - 1 and k.Based on this prediction the GA tries to choose u*(k) so as to

Optimize$x^p(k+1)$

The GA uses DNU to predict the result $x^p(k+1)$ of hypothetical

Controlinputs $u^h(k)$ and hence evaluate the fitness of $u^h(k)$.

At step *k*.Controller applies u*(k)

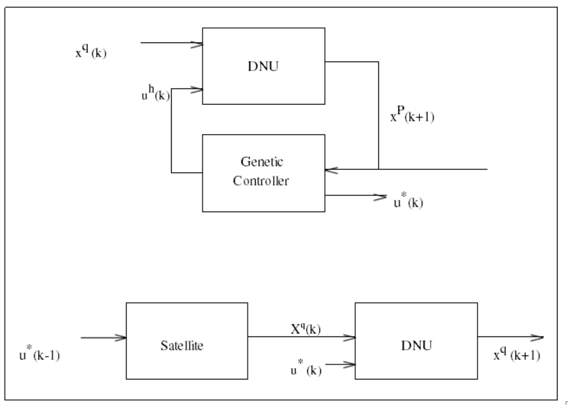

Figure1: The Control Architecture. Top: Between k-1 and k the DNU uses xq(k) and hypothetical control inputs$u^h(k)$. Bottom: When $t = k\ \Delta t$, x(k) is known and the DNU predicts $x^q(k+1)$.

DT-QNU for Satellite Identification

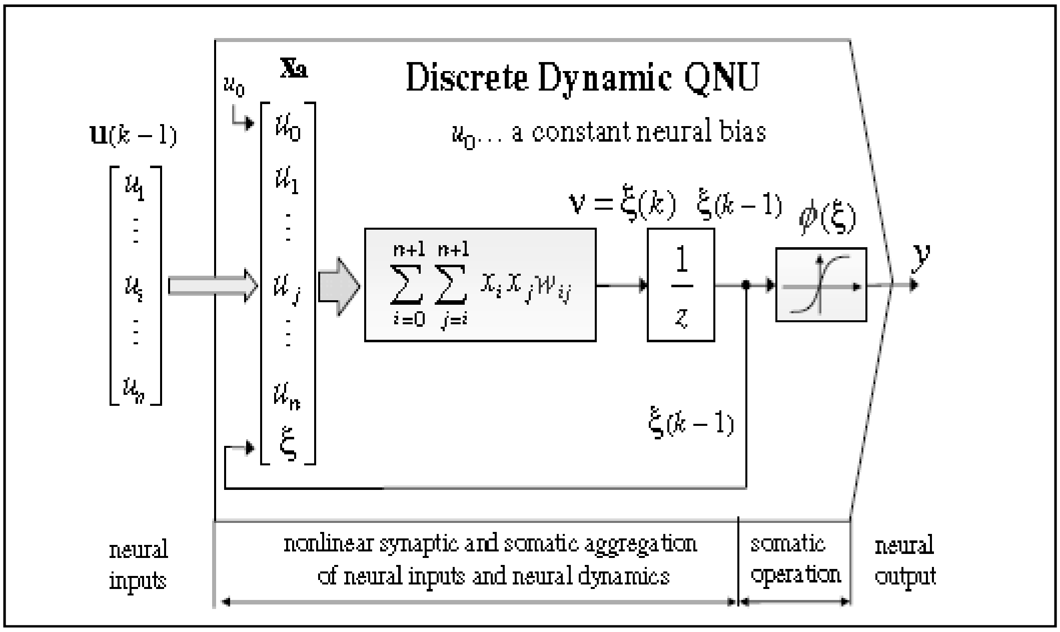

Figure 2: Discrete-time Quadratic Dynamic Neural Unit.

As shown in Figure (2) in the particular case of satellite attitude control system, which is represented by a vector, which contains discrete values in consecutive steps? Other input values are introduced by the dynamic feedback y_k and $_{(k+1)}$, and the threshold constant u_0. Thus we have the input vector with four values Eq. (4.4). The input vector enters the aggregation function Eq.(4.5) neural units, so that after the breakdown of the aggregate functions depending on the number of inputs to the internal functions of the neural units contain sums of products of different weights to specific neural inputs. Eq.(4.6) shows the broken aggregate function.

Defining the augmented vectors of neural inputs and neural weights, the synaptic operation for neural unit with DT-QNU is given as

$$f_{QNU} = \boldsymbol{x}_{\alpha} \cdot W \cdot \boldsymbol{x}_{\alpha}^{T} \tag{1}$$

Where

$$\boldsymbol{x}_{\alpha} = [x_0\, u_{(k)}\, y_{(k)}\, y_{(k+1)}]^T \tag{2}$$

$$f_{QNU} = \sum_{i=0}^{n-1}\sum_{j=i}^{n-1} x_i x_j w_{ij} \tag{3}$$

$, kde\, n = 4$

Then from the mathematical model

$$f_{QNU} = w_{00} + w_{01}u_{(k)} + w_{02}y_{(k)} + w_{03}y_{(k+1)} + w_{11}u_{(k)}^2 + w_{12}u_{(k)}y_{(k)} + w_{13}u_{(k)}y_{(k+1)} + w_{22}y_{(k)}^2 + w_{23}y_{(k)}y_{(k+1)} + w_{33}y_{(k+1)}^2 \qquad (4)$$

Neural weights matrix is given in (1).Complete the general registration of array aggregate functions is given in (2) and specific matrix notation for the discrete dynamic QNU is given in (4).

$$W = \begin{bmatrix} w_{00} & w_{01} & w_{02} & w_{03} \\ 0 & w_{11} & w_{12} & w_{13} \\ 0 & 0 & w_{22} & w_{23} \\ 0 & 0 & 0 & w_{33} \end{bmatrix} \qquad (5)$$

$$f_{QNU} = \begin{bmatrix} u_0 & u_{(k)} & y_{(k)} & y_{(k+1)} \end{bmatrix} \cdot \begin{bmatrix} w_{00} & w_{01} & w_{02} & w_{03} \\ 0 & w_{11} & w_{12} & w_{13} \\ 0 & 0 & w_{22} & w_{23} \\ 0 & 0 & 0 & w_{33} \end{bmatrix} \cdot \begin{bmatrix} u_0 \\ u_{(k)} \\ y_{(k)} \\ y_{(k+1)} \end{bmatrix} \qquad (6)$$

$$f_{QNU} = \begin{bmatrix} u_0 & u_{(k)} & y_{(k)} & y_{(k+1)} \end{bmatrix} \cdot \begin{bmatrix} w_{00} & w_{01} & w_{02} & w_{03} \\ 0 & w_{11} & w_{12} & w_{13} \\ 0 & 0 & w_{22} & w_{23} \\ 0 & 0 & 0 & w_{33} \end{bmatrix} \cdot \begin{bmatrix} u_0 \\ u_{(k)} \\ y_{(k)} \\ y_{(k+1)} \end{bmatrix} \qquad (7)$$

Calculation of increases of neural weights in matrix notation, for a particular discrete dynamic QNU, given in (8).

$$\Delta W_i = \mu \cdot e \cdot \begin{bmatrix} \frac{\partial f_{QNU}}{\partial w_{00}} & \frac{\partial f_{QNU}}{\partial w_{01}} & \frac{\partial f_{QNU}}{\partial w_{02}} & \frac{\partial f_{QNU}}{\partial w_{03}} \\ 0 & \frac{\partial f_{QNU}}{\partial w_{11}} & \frac{\partial f_{QNU}}{\partial w_{12}} & \frac{\partial f_{QNU}}{\partial w_{13}} \\ 0 & 0 & \frac{\partial f_{QNU}}{\partial w_{22}} & \frac{\partial f_{QNU}}{\partial w_{23}} \\ 0 & 0 & 0 & \frac{\partial f_{QNU}}{\partial w_{33}} \end{bmatrix} = \mu \cdot e \cdot \begin{bmatrix} 1 & u_{(k)} & y_{(k)} & y_{(k+1)} \\ 0 & u_{(k)}^2 & u_{(k)}y_{(k)} & u_{(k)}y_{(k+1)} \\ 0 & 0 & y_{(k)}^2 & y_{(k)}y_{(k+1)} \\ 0 & 0 & 0 & y_{(k+1)}^2 \end{bmatrix} \qquad (8)$$

Basic Genetic Algorithm

The basic GA used in this study and GA flow chart Figure (3) as well is as follow:

[Start] Generate random population of n chromosomes (suitable solutions for the

problem)
[Fitness] Evaluate the fitness *f(x)* of each chromosome *x* in the population
[New population] Create a new population by repeating following steps until the new population is complete
[Selection] Select two parent chromosomes from a population according to their fitness (the better fitness, the bigger chance to be selected)
[Crossover] With a crossover probability cross over the parents to form a new offspring (children). If no crossover was performed, offspring is an exact copy of parents.
[Mutation] With a mutation probability mutate new offspring at each locus (position in chromosome).
[Accepting] Place new offspring in a new population
[Replace] Use new generated population for a further run of algorithm
[Test] If the end condition is satisfied, stop, and return the best solution in current population
[Loop] Go to step 2

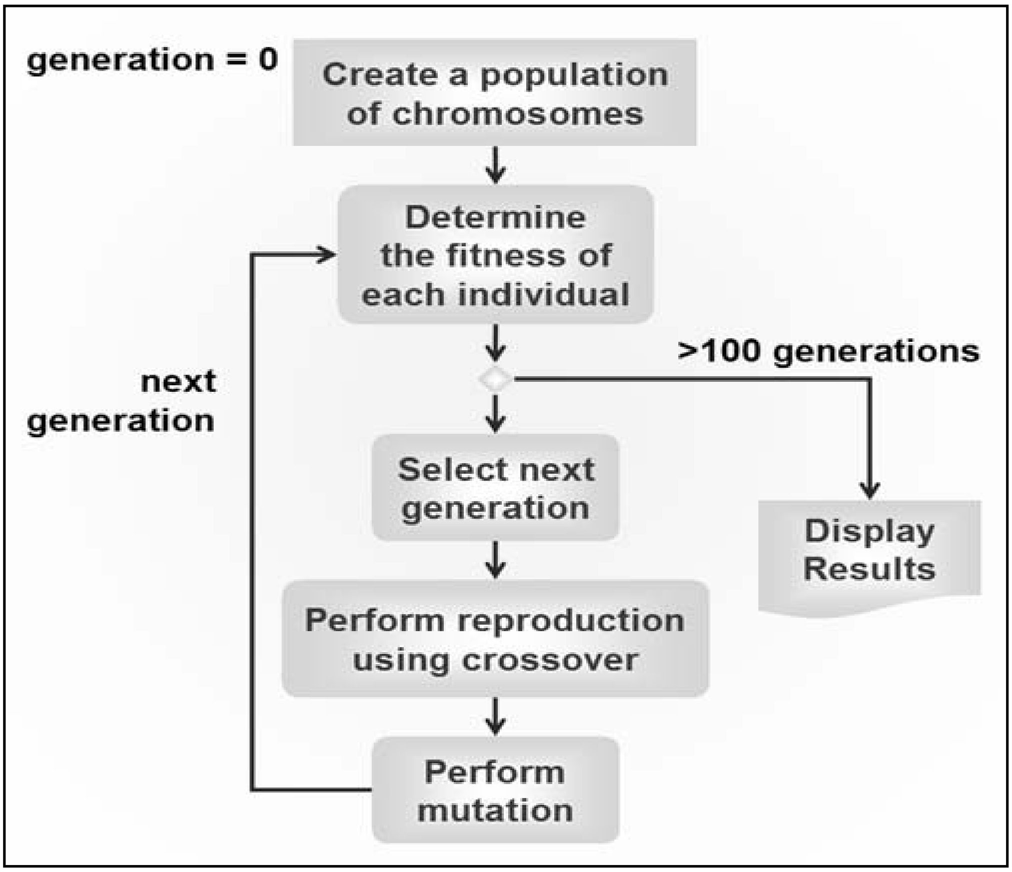

Figure 3: Flow Chart of The basic Genetic Algorithm

Computer Simulation and Results of Neuro-Genetic approach for Satellite Attitude Control Problem

The function of the Genetic Algorithm is to optimize the choice of control thruster torques at any given moment. This amounts to a time constrained locally optimal solution to an inverse kinematic problem. Suppose, for example, that the target state for the system is $\varphi = 0$, $\dot{\varphi} = 0, \theta = 0, \dot{\theta} = 0$ and the attitude and angular rotation about the third axis are unspecified. With this target in mind, one possible choice of goal is to use the GA at any given moment to choose the control torques (G_1, G_2, G_3) so as to minimize the function

$$F(G_1, G_2, G_3) = |\varphi| + |\dot{\varphi} + \varphi| + |\theta| + |\dot{\theta} + \theta| \qquad (4.29)$$

At the next sensor sample. Introduction of terms like $|\varphi + \dot{\varphi}|$ is motivated by two factors. First, if the angular velocities are initially high these terms will dominate, and the emphasis of the corresponding control actions will be mostly aimed at reducing them. Second, as the system approaches the target state these terms will act as damping so as to avoid overshooting the target state. Many other choices which accomplish the same goals are possible. The GA will attempt to do this by maximizing the fitness function

$$\mathrm{v}(\mathrm{G}_1, \mathrm{G}_2, \mathrm{G}_3) = \frac{1}{1+\mathrm{F}} \qquad (9)$$

Spin Stabilization of a Satellite about a Stable Axis

As shown in Figure (6), we assume, that for some unknown reason (damage), a satellite with specified dynamics, changes its characteristics so that the moments of inertia become I_x = 1150, I_y = 23100 and I_z = 23000.During the period where the system dynamics change, unknown forces lead it to the state ($\omega_1, \omega_2, \omega_3$) = (3, 2, 1), (φ, θ, Ψ) = (2, 1, 3). The goal is to detumble the satellite about the *x*, *y* body axes, spin it about the *z* body axis, and reorient it, so that φ, θ become minimum.Population size is one of the mostimportant parameters [57]. If it is too low the genetic algorithm will have to few solutions to alter a good result; if it is too high the performance impact may be too great so its takes longer time to reach a good solution.population_ size := 50.A lower selection pressure is recommended in the start of the genetic search; while a higher selection pressure is recommended at the end in order to narrow the search space [58].The study has chosen to follow the recommendations from De Jong and have used a 1-point crossover and normal mutation with a crossover rate of 0.6 and mutation rate of 0.001 to be used in the experiment.

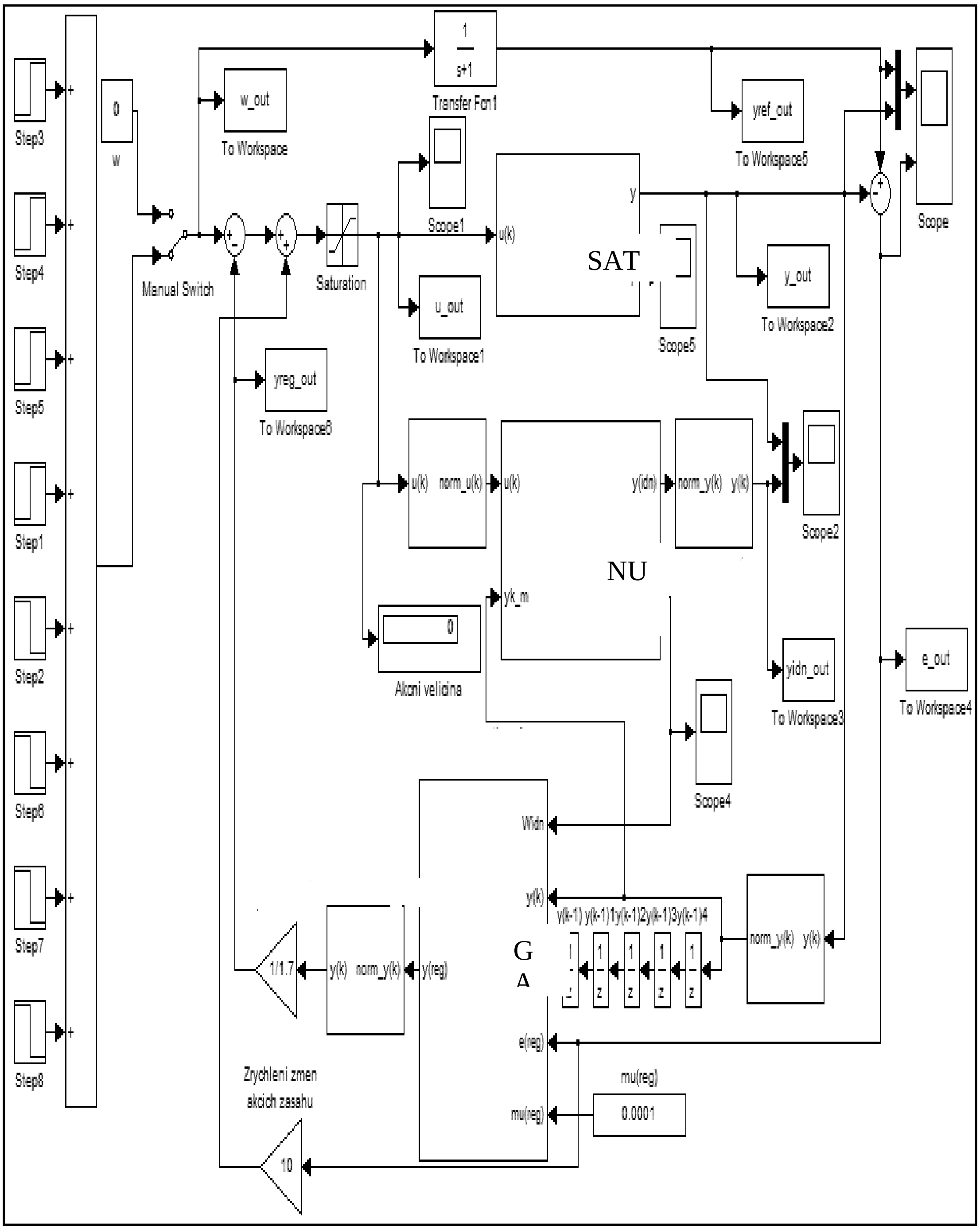

Figure 4: Block diagram of NU-Genetic approach Controller

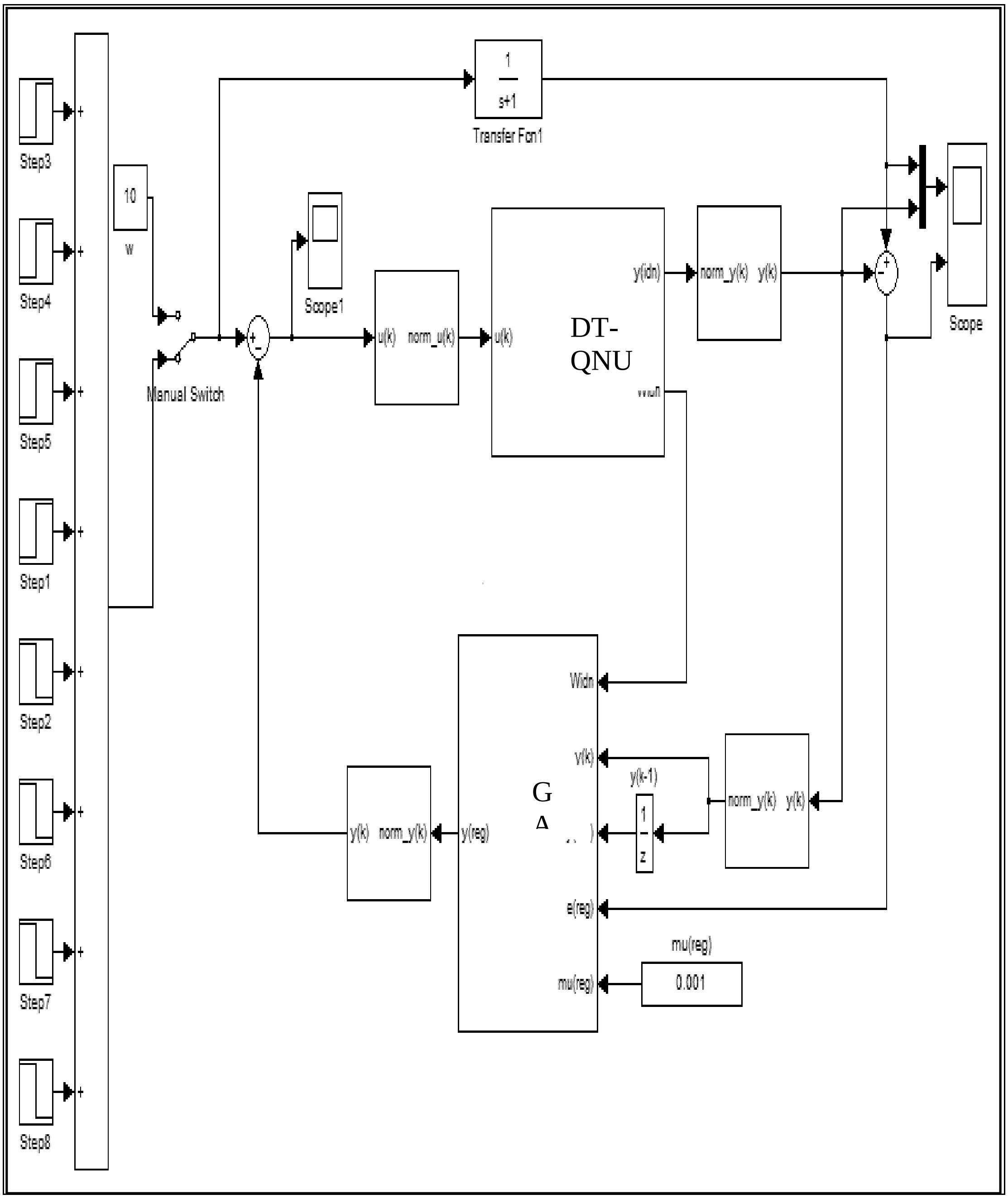

Figure 5: Block diagram of DTQN-Genetic approach Controller

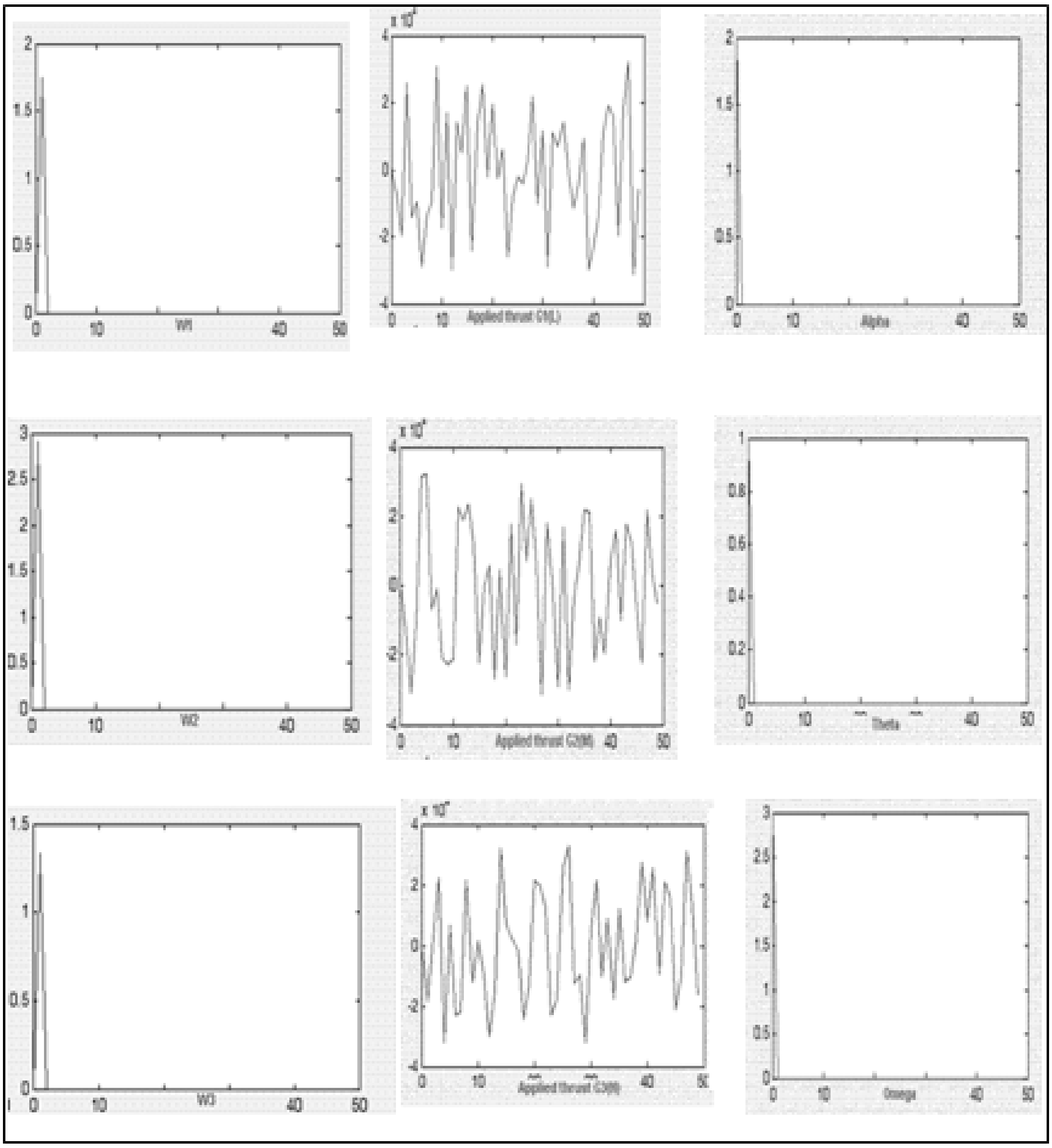

Figure 6: Angular velocities , Orientation angles and applied Thrusts during The application of DTQN-Genetic controller for Satellite about a stable axis

Spin Stabilization of a Satellite about Unstable Axis

In Figure (7) , this section the task of stabilizing a satellite (rigid body) about an unstable axis is considered. The moments of inertia of the satellite are I_x = 1150, I_y = 23000 and I_z = 23100. Simple rotation about the *z* body principal axis is *unstable* by the 'Tennis Racquet' theorem, since it corresponds to the intermediate principal axis $I_x<I_z<I_y$*[59]* and [60]. Thus in this case if the body is rotating about its *z* axis, a very small disturbance may produce a very great change in the subsequent motion [61] and[62].

The goal in this simulation is to spin stabilize the satellite about its *z* (unstable) axis. Thus the target state of the system is set to (φ, θ, Ψ) will be minimum. According to this a fixed spin of $\omega_3 = 1.0$ is specified. The initial conditions are:$(\omega_1, \omega_2, \omega_3)$ = (1.7494, 2.9092, 1.3276) , (φ, θ, Ψ) = (2, , 1, 3).

The objective function for the Genetic controller is specified to be:

$$F(G_1, G_2, G_3) = |\varphi| + |\dot{\varphi} + \varphi| + |\theta| + |\dot{\theta} + \theta| + |\dot{\psi} - 1.0|$$

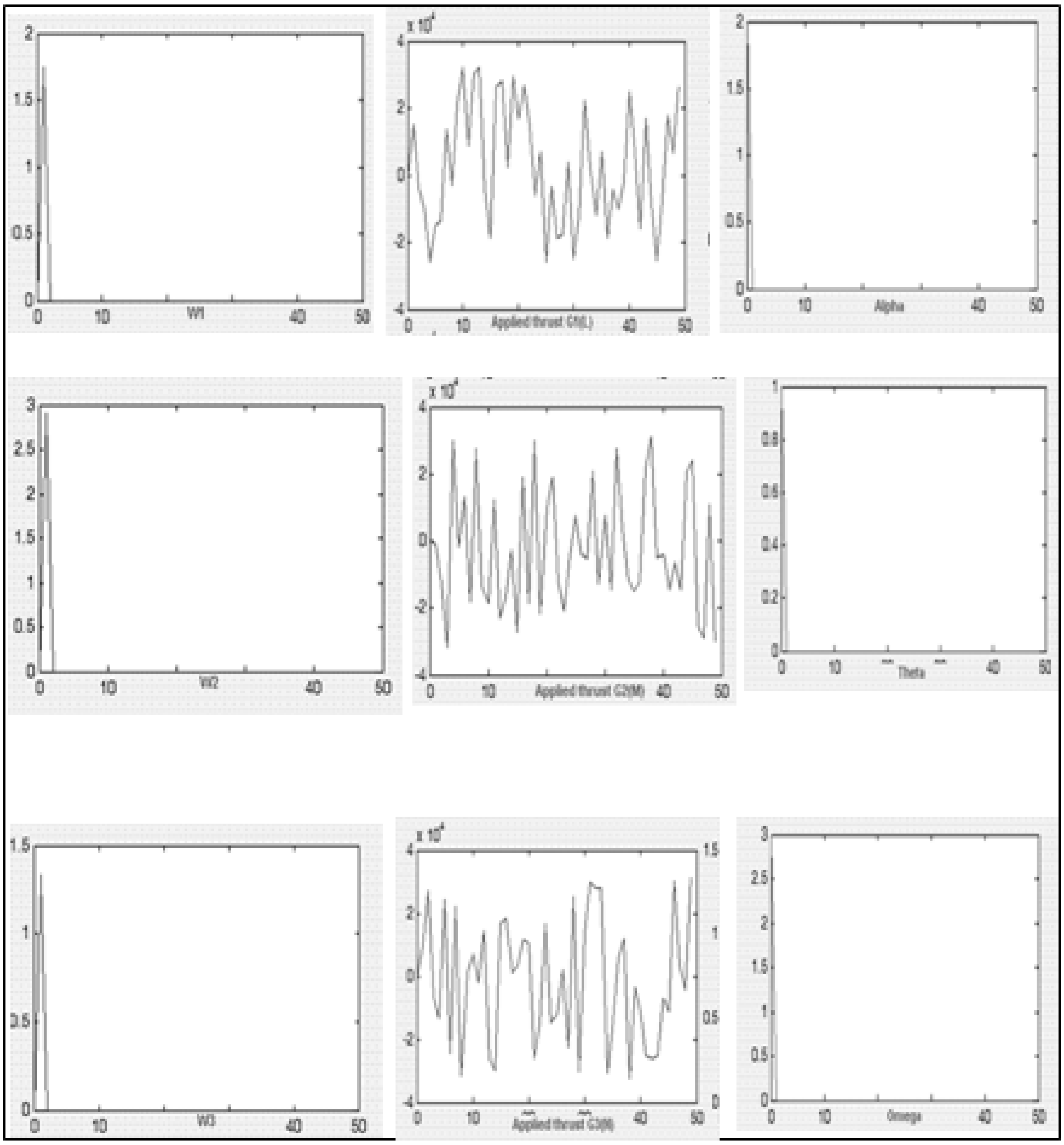

Figure 7: Angular velocities, Orientation angles and applied Thrusts during the application of DTQN-Genetic controller for Satellite about unstable axis

Spin Stabilization of a Satellite about Unstable AxisSubject to Sensor Noise (Robustness Test)

In igure (8) , we assume, that for some unknown reason (damage), a satellite with specified dynamics, changes its characteristics so that the moments of inertia become $I_x = 1150$, $I_y = 23100$ and $I_z = 23000$ [64].

During the period where the system dynamics change, unknown forces lead it to the state $(\omega_{1,}\, \omega_{2,}\, \omega_3) = (1.8, 2.7, 1.4)$, $(\varphi, \theta, \Psi) = (2, 1, 3)$.

$$F(G_1, G_2, G_3) \quad |\varphi| + |\dot{\varphi} + \varphi| + |\theta| + |\dot{\theta} + \theta| + |\psi - 1| + 0.01\, |\dot{\psi} + \psi - 1| \tag{10}$$

The goal is to spin stabilize the satellite about the *z* body axes, which is stable target state since the spin is about the axis having largest moment of inertia. Thus the target state of the system is set to (φ, θ, Ψ) to minimum values.

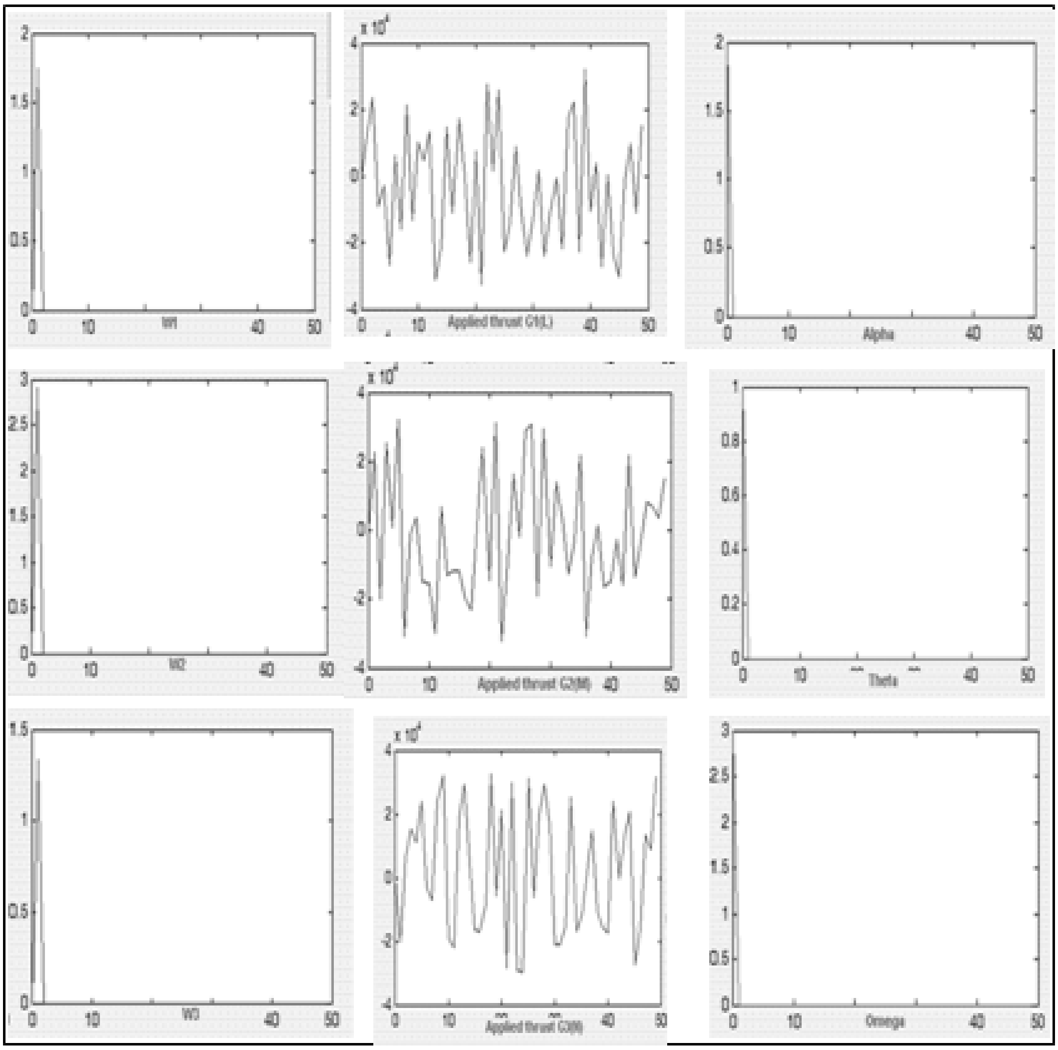

Figure 8: Angular velocities, Orientation angles and applied Thrusts during the application of DTQN- Genetic controller for Satellite about unstable axisSubject to sensor noise

Discussion of Simulation Results for Satellite Stability

The application of the genetic adaptive control architecture, leads to the situation described by Figure(6) show the evolution in time of the angular velocities $\omega_{1,}$ $\omega_{2,}$ about the *x, y* body axes respectively. The genetic controller soon leads both to the pre-specified value of zero. The third angular velocity is arbitrary, since it was unspecified in the control objectives.

Figure (6) show the reorientation of the satellite for the angles φ, θ during the application of the genetic controller. While these are becoming minimum values, the satellite is rotating about its *z* axis. It should be noted that the controller not only leads the system to a desired state, but it maintains this state afterwards.

The applied thrusts during the genetic control of the satellite are shown in Figure (6). We observe that during the time that the angular velocities are large the thrusts vary very rapidly, so that in some situations they can be seen as applying a kind of *bang-bang control*. As soon as the angular velocities obtain small values, the required and applied thrusts G_1, G_2, become ‘smooth’. The third thrust G_3 is not subject to evolutionary pressure near the target state and consequently has no incentive to become small. This is a result of the particular choice of objective function in this case - the target state is not fully specified.

We speculate that to some extent, at least for the attitude control problem, the discontinuous nature of the control solutions found by the genetic algorithm may be an artifact of the particular choice of objective function. The description of orientation in terms of φ, θ, Ψ is modulo 2Π and the objective function takes no account of this fact. Discontinuities might therefore be expected, particularly for large angular velocities. We regard it as a matter of considerable interest to investigate constraints on the genetic algorithm which may lead, where possible, to smoother solutions. Particularly because intuition suggests that highly discontinuous control solutions, with rapid sign changes of the torques, are liable to be energy inefficient.

Any method of direct neural inverse control is inevitably going to encounter this problem in some cases. Training a back propagation network requires training data, and if this data is elicited from a discontinuous control strategy one can expect severe problems in successfully training the network. In contrast, our experiments suggest that an (unconstrained) genetic algorithm will find very good (in the sense that the target is acquired rapidly) solutions to the inverse kinematic problem, even if these form a discontinuous function over time. Any quest for a smooth, energy minimal, adaptive control strategy will, in any case, inevitably involve a tradeoff of energy consumption against time-to-target. We plan to address these issues in later work.

Discussion of Simulation Results for Satellite Instability

Figure (7) shows the evolution in time of the angular velocities about the *x, y, z* body axes, respectively, during the application of the genetic controller. The controller soon leads two of them to the pre-specified value of minimum and the third to the pre-specified value of one. Once this is achieved the controller maintains these angular velocities.

In Figure (7) the reorientation of the satellite for the angles φ, θ during the application of the controller is shown. Whilst these are becoming minimum values, the satellite is rotating about its *z*axis . We observe that the controller not only reorients the satellite, but it maintains this reorientation.The applied thrusts during the genetic control of the satellite are shown in Figure (7).

Discussion of Simulation Results for Satellite Robustness Test

Noise of 10% -20% of the current sensor values (following a uniform distribution) is added to the sensor values [63] produced by the simulator, i.e. to the angular velocities ($\omega_1, \omega_2, \omega_3$) about the body and the inertial orientation angles (φ, θ, Ψ). Thus at any given time the controller has only imprecise knowledge of the actual system state.

The choice of the objective function needs some care. Since noise is present, when the system is near the target state much of the error will be due to noise and we should like to reduce 'hunting' (i.e. over-energetic control torques) and thus the long term energy expenditure of maintaining the target state. Consequently we want to smooth the angular acceleration near the target state. One way (amongst many) to achieve this is to introduce a smoothing term which forces $\ddot{\psi} + \dot{\psi} - 1$ near the target state. Thus our objective function is chosen to be

$$F(C_1, C_2, C_3) = |\varphi| + |\dot{\varphi} + \varphi| + |\theta| + |\dot{\theta} + \theta| + |\dot{\psi} - 1| + 0.01\,|\ddot{\psi} + \dot{\psi} - 1| \tag{11}$$

at the next sensor sample. This presupposes additional sensors for angular acceleration and would involve adding an extra output $\ddot{\psi}$ to the LPN predictor. For the present purpose, assuming the hypothetical thrusts we take a value of $\ddot{\psi}$ provided by the simulator. Introduction of terms like $|\varphi + \dot{\varphi}|$was motivated by two factors. First, if the angular velocities are initially high these terms will dominate, and the emphasis of the corresponding control actions will be mostly aimed at reducing them. Second, as the systems approaches the target state these terms will act as *damping* so as to avoid overshooting the target state. Many other choices which accomplish the same goals arepossible. The coefficient 0.01 for the higher order smoothing term makes this term small when the system is far from the target state, and thus speeds up acquisition of the target state; effectively the angular acceleration is not considered near the start of the simulation. As the system approaches the target state the first five terms in the objective function become small and the last term, the smoothing term, becomes significant.

In all the simulations the GA will attempt to minimize the objective function by maximizing the fitness function . The application of the genetic adaptive control architecture, described by Figure (8), with the objective function given by (10), leads to the situation described by Figure (8) , shows the evolution in time of the angular velocities $\omega_1, \omega_2, \omega_3$ about the *x, y, z* body axes respectively. The genetic controller soon leads both ω_1 and ω_2 to the pre-specified value of zero and ω_3 to one. Figure (8) shows the reorientation of the satellite for the angles φ, θ during the application of the genetic controller. While these are becoming zero, the satellite is rotating about its *z* axis, Fig. (4.40). It should be noted that the controller not only leads the system to a desired state, but it maintains this state afterwards.

The applied thrusts during the genetic control of the satellite are shown in Figure (8). observing that during the time that the angular velocities are large the thrusts vary very rapidly, so that in some situations they can be seen as applying a kind of *bang-bang control*. As soon as the angular velocities obtain small values, the required and applied thrusts G_1, G_2, G_3 become small and somewhat smoother. Not surprisingly the presence of significant noise reduces the smoothness of the control actions near the target compared with the previous test.

GA was successfully applied to optimise the choice of control thruster torques at any given moment. for DTQN which was successfully applied to control the attitude of a satellite. This amounts to a time constrained locally optimal solution to an inverse kinematic problem. With the use of multiple initial conditions in determining the objective function, the designed controller is shown to be stable in a broad rangeof the operating conditions. The advantage of this particular proposal lies principally in the fact that the architecture can in principle be applied to non-linear control problems in which the inverse kinematics are ill posed and potentially good control solutions may even be discontinuous functions of time, i.e. it is perfectly genera. Our experiments raised some interesting questions. It seems likely that for the particular system considered there are control solutions which may acquire the target state in approximately the same time interval, but which are less discontinuous and more energy efficient. Of course, energy efficiency will usually involve a tradeoff against time to- target. We think it probable that by suitably constraining the genetic algorithm search it may be possible to improve energy efficiency for the attitude control problem. In general the question of using a genetic algorithm formulti-objective optimization is an area requiring further research.

CONCLUSIONS

A novel DTQN-G theory for identification and control of satellite attitudeusing dynamic non-linear complex systems was established.DT-QNU was presented as a Neuro-identifier for the control of a complex system such as satellite attitude control.A novel class of Genetic Algorithm (GA) controller code using computer programming and MATLAB & Simulink simulations was designed.Pseudo code functionality was established as well the evolution solution of sample problem.Optimization of control thruster choice was achieved using computer simulations.

Directlyestimating the effectiveness of this genetic algorithm is rather difficult because the true optimum isunknown. In principle it is possible to obtain an upper bound for the achievable fitness from energy considerations: given the fact that available thruster torques is bounded (and no external torques is acting upon the body) only system states in a certain region about the initial state are in fact reachable. However, the true test of the genetic algorithm is whether it produces sufficiently good solutions to achieve successful control and, as it was seen, by this test the genetic algorithm performs very well.

The practical application for satellite attitude control as well as small changes of variability (level of chaos) in satellite orientations and angular velocities was founded and discussed.Examination and verification of the simulation experiments in which speculative DTQN-G architectures would acquire and maintained an arbitrary target state with no prior knowledge of system dynamics for stable and unstable target states was established DTQN-G can handle well-controlled nonlinear system in its entirety satellite controlled variable. The Neuro-identifier design was first necessary to identify the system satellite. To identify the selected DT-QNU the dynamics of second Regulations, well-managed an approximation of real data available of satellite. Results obtained from the identification system was then required under the mathematical description used for DT-QNU, which was engaged in state custody as a feedback adaptive controller itself. Special interventions are supported by the introduction of proportional components. It is clearly demonstrated very good and rapid regulation of (GA) controller. In addition to good control is the use of GA-controller further advantages. Neuro-Identifier using the identification system adjusts itself, even when it is not fair system described by any mathematical model. For the GA controller thus need only know the inputs and outputs of the real system and the system itself does not need to know.

For the GA also discussed the fact that the ability of good regulation had no (or very negligible) influence change in the angular velocities in the satellite. With each change in the angle of angular velocities would be re-tune GA controller. GA-controller is able to absorb the entire dynamics of the system.During the practical applications has also been shown that the control system Satellite depends more on the size of the changes desired quantity rather than depth of immersion satellite. Immersion satellite and its initial position, however, have to conduct a regulatory impact. These facts are due to system nonlinearities. Another important finding was that the GA controller for any deviation or noise, i.e. Fault simulation at the action values immediate reaction by running the actuator, which refers to his immediate reaction. The possibility of using adaptive GA controller for other nonlinear systems is very promising. The advantage is the ability to use it even for unknown real system. In the future it would be appropriate at this issue further focus on the size of the changes requested variables, not only to the desired depth or precise identification systems such as real-time identification.

Examination of simulation experiments in which a speculative DTQN-G architecture was applied to the adaptive attitude control problem for arbitrary transitions of system states. The practical applications tested the ability of the system to acquire and maintain an arbitrary target state with no prior knowledge of the system dynamics. This was achieved for both dynamically stable and unstable target states. By themselves these two experiments are encouraging (especially since simple objective functions were used for the genetic algorithm) but are by no means definitive: real systems should be able to cope with a variety of complications one of which is inaccuracies in the sensors.

Establish the robustness of DTQN-Garchitecture versus noise signal that would be introduced and added to the sensor data was done.

In the third experiment the robustness of the architecture was tested by introducing 15% noise added to the sensor data. The system coped very effectively with this additional difficulty.

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